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Predicting Wildlife Distributions And Resilience Under Alternative Futures

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PREDICTING WILDLIFE DISTRIBUTIONS AND RESILIENCE UNDER ALTERNATIVE FUTURES

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ABSTRACT

In the northeastern United States, population expansion, climate change, land use, and land-use change all pose serious concerns for wildlife. Understanding the impacts of climate and land-use change on species distributions can help inform conservation decisions. Unfortunately, empirical data on distributions are limited for many wildlife species, making conservation planning challenging. This dissertation focuses on the use of expert opinion data for modeling wildlife distributions and evaluating the impacts of future climate and land-use changes. First, I implemented expert elicitation techniques to collect wildlife occurrence data for harvested species (n = 10) in the New England region. I then used mixed-model methods to develop species distribution models (SDMs) and applied the models to the regional landscape to map species distributions relative to recent (2010) conditions. Second, I used a systematic scenario-based approach to estimate species future distributions and evaluate how two influential drivers of landscape change – socio-economic connectivity and natural resource planning – influenced distribution change and species richness. Third, I used the collection of baseline and scenario projected distribution maps to evaluate patterns of distribution change and isolate areas of greatest resilience for individual species. I also assessed resilience patterns in and out of the region's protected network and identified protected areas with the highest representation of species resilience. Together, these three studies demonstrate the utility of expert derived SDMs and scenarios for evaluating wildlife futures, emphasize the value of species-based resilience assessments, and generate tools that can inform proactive decision-making and collaborative, multi-scale conservation planning.

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CHAPTER 1: INTRODUCTION AND BACKGROUND

1.1. Aim & Scope

In the New England region of the northeastern United States (US), population expansion, industrial development, agriculture, timber harvest, and changing climate all pose concerns for wildlife and challenges for their management. With increasing rates of climate and land use change, environmental decision-makers in the northeastern US face three crucial yet unresolved questions: 1) How do environmental factors and policy drivers influence wildlife distributions? 2) How will changes in climate and land use impact the future distribution and resilience of wildlife species? And, 3) Will current patterns of land protection effectively conserve wildlife populations in the future? These questions form the basis of this dissertation.

This dissertation aims to advance an understanding of wildlife futures in the New England region by focusing on three primary objectives: 1) the development of broad-scale, spatially compatible species distribution models (SDMs) for harvested wildlife species (n = 10) in the New England region; 2) applying SDMs to estimate how scenario projected climate, forest management, and land-use changes impact future species distribution and species richness patterns; and 3) using scenario derived distribution change maps to evaluate spatial patterns in species resilience and protection throughout New England.

1.2. Background & Motivation

With human-dominated land uses expanding worldwide (Klein Goldewijk et al. 2011; Seto et al. 2012), robust multi-decadal warming of global surface temperatures (Hayhoe et al. 2018; IPCC 2014), and less than 15% of the world's terrestrial land under protection, natural ecosystems are increasingly susceptible to modification (UNEP-WCMC & IUCN, 2016). Changes in climate and land use patterns can alter the distribution and quality of habitat, availability of resources, and frequency and intensity of climate stressors (Díaz et al., 2019; Rustad et al., 2012). These environmental changes can substantially alter the distribution and persistence of wildlife species (Jetz, Wilcove, & Dobson, 2007; Sirami et al., 2017; Thomas et al., 2004; Warren et al., 2013). Human influences on climate and land use have already increased global extinction rates by an estimated 100–1,000 times the pre-human species extinction rates (Pimm, Russell, Gittleman, & Brooks, 1995). With spatial variation in climate and land use patterns, certain species and regions are more susceptible to future change.

New England is a 186,458 km^2 region in the northeastern US that encompasses six states – including Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont. As one of the most forested and densely populated regions in the country, New England is both an economically and ecologically important region (Dupigny-Giroux et al. 2018; Foster et al. 2010). However, this region is also undergoing relatively rapid changes in land cover composition, land use intensities, and climatic conditions (Foster 1992; Olofsson et al. 2016; Rustad et al. 2012; Thompson et al. 2013). With the modern pressures of a human population that has more than doubled over the last century (~107% increase; U.S. Census Bureau, 2019), forests throughout the region are in decline

(Olofsson et al., 2016). Moreover, in the last century the New England region has experienced an approximately 1 °C increase in average surface temperature and a 10 mm/decade increase in average annual precipitation (Hayhoe et al. 2007; Huntington et al. 2009). While these changes can have considerable consequences for wildlife – including altered species diversity, distribution, and abundance (DeGraaf & Yamasaki, 2001; Rustad et al., 2012; Thompson et al., 2013) – information gaps and uncertainty around climate and land use trajectories currently limit our understanding of how future changes will impact wildlife species.

Rapidly changing environments present management challenges for federal and state agencies charged with maintaining viable wildlife populations. Limited funding and resources preclude the management of all wildlife species, highlighting the need for focal species strategies (U.S. Fish & Wildlife Service, 2015). In New England, game species typically attract public attention, help generate funding for agencies, and can trigger management activities on the landscape (Lueck, 2005; Perschel, Giffen, & Lowenstein, 2014). With diverse life histories and habitat requirements, game species can act as focal surrogates for the protection of non-game wildlife and overall biodiversity (Caro, 2010). Improving our understanding of game species may alleviate monitoring demands and help facilitate the conservation of a broader range of taxa.

Species distribution models (SDMs) – or models that describe how a species is distributed across an area of interest – can play a critical role in supporting spatial conservation planning (Addison et al., 2013; Margules & Pressey, 2000). By relating species occurrences to spatial environmental data, SDMs can predict measures of environmental quality for wildlife species through space and time (Franklin, 2010;

Guisan & Thuiller, 2005; Hegel, Cushman, Evans, & Huettmann, 2010; Pearce, Cherry, Drielsma, Ferrier, & Whish, 2001; Turner & Gardner, 2015). Unfortunately, due to current data limitations, regionally applicable SDMs are lacking for wildlife in New England. In order to develop SDMs that capture a geographic region's complex and variable environmental conditions, broad-scale distribution data are required for wildlife species (James, Choy, and Mengersen 2010; Murray et al. 2008; Pearce et al. 2001; Turner and Gardner 2015).

Expert elicitation – the process of retrieving and quantifying expert knowledge – is used in many fields to gain information when empirical data are limited, unavailable, or difficult to obtain. In an environmental context, expert opinion data have been used by numerous studies to assess the status of wildlife species (Clark, Applegate, Niles, & Dobkin, 2006), evaluate habitat suitability and model wildlife distributions (Aylward et al. 2018; Mouton, De Baets, and Goethals 2009; Murray et al. 2009; Pearce et al. 2001; Yamada et al. 2003), inform the relocation of wildlife (Paterson et al., 2008), and identify habitat linkages and potential movement corridors for wildlife species (Aylward et al., 2018; Clevenger, Wierzchowski, Chruszcz, & Gunson, 2002). Elicitation offers a relatively quick and inexpensive approach to data collection that is particularly valuable to large-scale studies of rare or poorly documented species (James et al., 2010). Developing SDMs from expert opinion data can help overcome the limitations and challenges of observational studies (e.g., small sample size, small study region, imperfect detection, etc.), and yield models that more accurately quantify spatial relationships between species occurrence and environmental factors. SDMs that capture the influence of climate and land use on regional wildlife dynamics can help inform priority conservation and management activities across the region (James, Choy, and Mengersen 2010; Murray et al. 2008; Pearce et al. 2001).

Effective long-term conservation and management strategies require a comprehensive understanding of wildlife species' potential responses not only to environmental stressors and disturbances, but also to future policy and management actions (Chambers, Allen, & Cushman, 2019). Scenarios can be used to better understand the drivers and consequences of change for wildlife species (McGarigal, Compton, Plunkett, Deluca, & Grand, 2017; Pereira et al., 2010; G. D. Peterson, Cumming, & Carpenter, 2003; Thompson et al., 2016). Scenario-planning methods provide a powerful way to explore and understand hypothetical futures while explicitly acknowledging their inherent uncertainty (Henrichs et al., 2010; McBride et al., 2017; G. D. Peterson et al., 2003). In New England, scenario-based studies have been initiated to improve understanding and anticipate future trajectories of land use and natural infrastructure (Duveneck & Thompson, 2019; McBride et al., 2017; McGarigal et al., 2017; Thompson, Plisinski, Olofsson, Holden, & Duveneck, 2017). For example, the Designing Sustainable Landscapes project developed models to simulate a current trends scenario for landscape change in the northeastern US and assessed the scenario associated ecological impacts (McGarigal et al., 2017). Another study, the New England Landscape Futures Project (NELFP), developed five scenarios that simulate different landscape futures for the New England region.

The NELFP scenarios were collaboratively designed by stakeholders, modelers, and researchers throughout New England and represent five plausible trajectories for how New England's landscape may change over fifty-years (2010 to 2060). These scenarios include a simulation based on recent trends (Duveneck & Thompson, 2019; Thompson et al., 2017), and four alternative scenario simulations of landscape change (Thompson et al., 2019). The alternative scenarios were built around two uncertain, yet highly influential drivers of landscape change: 1) Natural Resource Planning & Innovation (NRPI) – the extent to which the government and private sector invest in proactive land use planning, ecosystem services, and technological advancements for resource use – and 2) Socio-Economic Connectedness (SEC) – the extent of local or global connectivity in population migration, culture, economic markets, and climate policy (McBride et al., 2017; Thompson et al., 2019). The NELFP scenarios capture a wide range of possible future conditions and provide informed spatial projections of climate, forest structure and composition, development, and agriculture, making them well suited for spatially oriented wildlife assessments. With uncertainty around policy drivers and environmental trajectories of change, SDMs and scenario-based assessments can generate important spatially-explicit insight and advance understanding of the complex, dynamic systems that affect wildlife now and in the future (Henrichs et al., 2010; G. D. Peterson et al., 2003).

1.3. Dissertation Overview

This dissertation provides novel tools and approaches for evaluating the spatial consequences of climate and land use change for wildlife species. The following body of work is organized in four successive chapters, each building on the work and results of the previous chapters.

Chapter 2 focuses on the use of expert elicitation methods to develop species distribution models (SDMs) and regional distribution maps for game species (n = 10) in

New England. In this study, we administered a web-based survey that elicited opinions from wildlife experts on the likelihood of species occurrence throughout the New England region. We collected 3,396 probability of occurrence estimates from 46 experts and used mixed-model methods to develop SDMs. The models were applied to the regional landscape to estimate species distributions and to identify spatial patterns in species richness. This study provides geographically consistent and ecologically relevant SDMs for wildlife species in New England.

Chapter 3 implements a scenario-based approach to estimate the future distribution of targeted wildlife species and evaluate the influence of policy drivers on species distribution change. In this study, we used scenarios developed by the New England Landscape Futures Project to simulate species distributions under various trajectories (n = 5) of landscape change. We assessed how two policy drivers (i.e., SEC and NRPI) influenced distribution change and regional species richness patterns and identified the drivers with the greatest influence on individual species and the focal wildlife community.

Chapter 4 demonstrates the value and versatility of SDMs and scenario-planning for evaluating spatial resilience patterns of wildlife species in New England. This study presents a novel approach for assessing species resilience – built from a comprehensive understanding of species occurrence patterns under multiple landscape futures (i.e., the NEFLP scenarios). We applied a systematic approach to identify areas where individual wildlife species were consistently resilient across all scenarios and evaluated trends in resilient areas and existing land protection. This collective information advances our understanding of species spatial resilience and can aid regional conservation and management decisions.

Chapter 5 provides a summary of the findings and main conclusions of this dissertation. This chapter also reviews the limitations of the tools and assessments presented in this dissertation and highlights the relevance of this work for future conservation and management planning.

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CHAPTER 2: PREDICTING WILDLIFE DISTRIBUTION PATTERNS IN NEW ENGLAND USA WITH EXPERT ELICITATION TECHNIQUES

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2.1. Abstract

Understanding the impacts of landscape change on species distributions can help inform decision-making and conservation planning. Unfortunately, empirical data that span large spatial extents across multiple taxa are limited. In this study, we used expert elicitation techniques to develop species distribution models (SDMs) for harvested wildlife species (n = 10) in the New England region of the northeastern United States. We administered an online survey that elicited opinions from wildlife experts on the probability of species occurrence throughout the study region. We collected 3,396 probability of occurrence estimates from 46 experts and used linear mixed-effects methods and landcover variables at multiple spatial extents to develop SDMs. The models were in general agreement with the literature and provided effect sizes for variables that shape species occurrence. With the exception of gray fox, models performed well when validated against crowdsourced empirical data. We applied models to rasters (30 x 30 m cells) of the New England region to map each species' distribution. Average regional occurrence probability was highest for coyote (0.92) and white-tailed deer (0.89) and lowest for gray fox (0.42) and moose (0.52). We then stacked distribution maps of each species to estimate and map focal species richness. Species richness (s) varied across New England, with highest average richness in the least developed states of Vermont (s = 7.47) and Maine (s = 7.32), and lowest average richness in the most developed states of Rhode Island (s = 6.13) and Massachusetts (s = 6.61). Our expert-based approach provided relatively inexpensive, comprehensive information that would have otherwise been difficult to obtain given the spatial extent and range of species being assessed. The results provide valuable information about the current distribution of

wildlife species and offer a means of exploring how climate and land-use change may impact wildlife in the future.

Key Words: AMSurvey; expert elicitation; harvested species, New England; occupancy; species distribution modeling (SDM).

2.2. Introduction

Changes in land cover (the ecological characteristics of the land), land use (how land is utilized), and climate patterns can alter the ecology and biological diversity of an area (Brown & Laband, 2006; Foley et al., 2005; Lindenmayer & Franklin, 2002; Vitousek, Mooney, Lubchenco, & Melillo, 1997). The New England region in the northeastern United States encompasses the states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont (186,458 km^2; Fig. 2.1), and has a long history of profound social, economic, and ecological changes (Dupigny-Giroux et al., 2018; Jeon, Olofsson, & Woodcock, 2014; Thompson et al., 2013). New England is currently the most forested and densely populated region in the country. However, this economically and ecologically important region (Dupigny-Giroux et al., 2018; D R Foster et al., 2010) is undergoing relatively rapid changes in land cover composition, land use intensities, and climatic conditions (David R. Foster, 1992; Olofsson et al., 2016; Rustad et al., 2012; Thompson et al., 2013). With modern pressures of a human population that has more than doubled over the last century (~107% increase; U.S. Census Bureau, 2019), forests throughout the region are in decline (Olofsson et al., 2016). Moreover, the New England region has experienced a 10 mm/decade increase in average annual precipitation and a ~1 °C increase in average temperature over the last century (Katharine Hayhoe et al., 2007; Huntington et al., 2009; Rogers & Young, 2014). In New England, these changes have significantly impacted the diversity, distribution, and abundance of wildlife (DeGraaf & Yamasaki, 2001; Rustad et al., 2012; Thompson et al., 2013).

Limited funding and resources preclude management of all wildlife species, highlighting the need for focal species strategies. A focal species strategy identifies and directs attention to key wildlife species, making it easier to track management and conservation success (U.S. Fish & Wildlife Service, 2015). In New England, game species typically attract public attention, help generate funding for agencies, and can trigger management activities on the landscape (Lueck, 2005). With diverse life histories and habitat requirements, game species can act as surrogates for the protection of non-game wildlife and overall biodiversity (Caro, 2010). For example, game species with large home ranges, such as the bobcat (*Lynx rufus*), often act as umbrella species benefiting other non-target species through their protection and management (Simberloff, 1998). Other game species such as moose (*Alces alces*) may act as indicator species signaling the effects of environmental changes (Caro, 2010). Because the annual harvest is often tracked through time and space (typically at the town level or within wildlife management units), localized monitoring programs are already in place for game species. Thus, using game species as focal species may alleviate monitoring demands and help facilitate the conservation of a broader range of taxa.

When developing a regional conservation effort, species distribution models (SDMs) – or models that describe how a species is distributed across an area of interest – can provide important information and predictive insight (Guisan & Thuiller, 2005; Pearce et al., 2001; Rustad et al., 2012; Turner & Gardner, 2015). Unfortunately, even for highly monitored game species, regional species distribution models for New England wildlife are lacking. Given that management is regulated at the state level, studies of harvested species are typically focused on single species and concentrated on local extents or on a state-by-state basis (Organ et al., 2012). Localized studies may fail to capture a geographic region's complex and variable environmental conditions and often overlook important landscape level influences (J. V. Murray et al., 2008; Turner & Gardner, 2015). Broad scale distribution data are needed to better capture the influence of climate and land-use change on regional population dynamics and inform priority conservation and management activities across the region (James et al., 2010; J. V. Murray et al., 2008; Pearce et al., 2001). Inadequate assessments of species distributions may contribute to 1) inefficient, expensive and unsustainable conservation and management practices, 2) declines in biodiversity, and 3) the loss of ecologically, economically, and culturally important species (Franklin, 2010).

To address these issues, we used expert elicitation methods to collect species probability of occurrence data for a set of managed wildlife species in New England. Our objectives were to: 1) Develop a regional, multi-species survey that collects species-specific probability of occurrence data at numerous sites across New England; 2) Conduct the survey with expert elicitation methods, in which experts were asked to report the probability of occurrence of target species at a subset of study sites; 3) Analyze results to develop SDMs with generalized linear mixed effect and stepwise modeling approaches; and 4) Map wildlife species regional distributions and identify areas of multispecies conservation interest. This approach allowed for quick and effective data collection and the generation of geographically consistent and ecologically relevant SDMs for wildlife species in New England. The SDMs provide insight into the factors that shape species' distributions and a means of better assessing the effects of management actions and landscape change on wildlife in the region. Our approach can be applied to other species, regions, and spatial extents, and is especially relevant to species of high management or conservation value and contexts in which little empirical data exist.

2.3. Methods

Study Area. The study area included the six New England states (Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and Maine) in the northeastern United States (Fig. 2.1). This region covers 186,458 km^2 with topography ranging from coastal plains to mountain peaks nearly 2,000 m above sea level. Climatic conditions vary by season and geographic location throughout the region. Long-term climate records indicate an average annual precipitation of 104 cm and monthly temperature ranging from 6 °C (Jan) to 19 °C (Jul) (Huntington et al., 2009).

The region supports a growing human population (ca. 14,735,000 in the 2016 U.S. Census) with three-quarters of the population concentrated in the major metropolitan areas of southern New England (U.S. Census Bureau, 2018). This uneven population distribution contributes to regional variability in land use patterns and intensities. Approximately 80% of the region is covered in forest (D R Foster et al., 2010). Forested regions are ecologically diverse with areas dominated by northern hardwood, spruce-fir, oak-hickory, and pine-oak forest types (Brooks, Frieswyk, Griffith, Cooter, & Smith, 1992; Duveneck et al. 2015). Development (9.3% of the region), agriculture (5.9% of the region) and water (12.3% of the region) constitute the majority of the non-forested landscape (Homer et al., 2015).

Focal Species. We elicited information and developed models for 10 commonly harvested species in New England (Table 2.1). The focal group included seven species in the Carnivora order (American black bear, bobcat, coyote, gray fox, raccoon, red fox, and striped skunk), two species in the Artiodactyla order (moose and white-tailed deer), and one species in the Galliformes order (wild turkey). We selected these species because they are frequently the target of wildlife management programs in New England.

Objective 1 – Develop wildlife survey

We developed a survey to capture expert opinions of the probability of occurrence of each species. The survey asked experts to evaluate a set of sites and provide an occurrence estimate for target species at each site (see below). Development of the survey involved: 1) identifying survey sites, 2) estimating site characteristics, and 3) selecting appropriate experts.

Survey Sites. Survey sites were U.S. Department of Agriculture (USDA) Forest Service Forest Inventory and Analysis (FIA) plot locations (see Bechtold and Patterson 2005). Forest inventory plots occur in all forested lands in the United States and are spatially distributed across a national base grid (hexagonal grid with a plot randomly located within each 6,000-acre hexagon; Bechtold and Patterson 2005). The New England region included 6,930 plots. Our sites were uniform circles, 3.14 km^2 in area (1-km radius), centered on the perturbed coordinates (see McRoberts et al. 2005) of all of these FIA plots. We used a 1-km radius in an effort to include diverse land cover within sites while also keeping the site small enough for survey participants (i.e., wildlife experts; see below) to accurately estimate occurrence.

Site Covariates. We compiled a comprehensive covariate list that incorporated all potentially important drivers of distribution based on a literature review of each species' behavior and ecology. Site-specific information for a total of 54 covariates was provided to experts during the elicitation survey (see below). These covariates included 47 land cover variables (32 associated with forest species and 5 associated with forest age), 3 topographic variables, and 4 climate variables (Appendix A.1). Covariate data were extracted and summarized for each site using the statistical computing language R (R Core Team, 2019) and the Geographic Information System, ArcGIS 10 (ESRI, Redlands, California, USA).

Experts. Wildlife experts were selected based on experience and qualifications. Baseline qualifications required experts to have a background in wildlife management, conservation, or related field, and strong knowledge of one or more of the focal species in the New England region. Experts were identified predominantly by their current and past research contributions, academic contributions, and work experience related to wildlife management and conservation. Professional wildlife biologists were recruited by contacting state and federal agencies. Additional experts – including experienced hunters and trappers – were identified according to their field-based knowledge and through expert nomination. All participation was voluntary; survey protocols were approved by the University of Vermont Institutional Research Board (IRB 17-0417).

Objective 2 – Conduct wildlife survey

New England Wildlife Survey. Expert opinion data were collected through a web-based survey interface developed by the Vermont Cooperative Fish and Wildlife Research Unit called AMSurvey (https://code.usgs.gov/vtcfwru/amsurvey). The survey tool was inspired by the 'Elicitator' framework developed by James et al. (2010) and consisted of three main sections, as described below.

Section 1. This section provided introductory information and a pre-survey questionnaire. Each expert was provided with written instructions, reference materials and a video tutorial to guide them through the elicitation process (see https://code.usgs.gov/vtcfwru/amsurvey/wiki for example materials). Experts were asked to identify their area of expertise (six possible regions, separated by state boundaries; multiple regions could be selected) and their target species of expertise (more than one species could be selected). Experts also completed a short pre-survey questionnaire, which focused on demographic information and the nature of their expertise (Appendix B.1).

Section 2. This section was the elicitation survey itself. A subset of the FIA sites (n = 30) were selected for each expert through a k-means clustering approach (Likas, Vlassis, & J. Verbeek, 2003). Sites within the user's spatial area of expertise were clustered into 30 groups based on site covariate values. Then, we randomly sampled one site within each of the 30 groups to create an expert-specific subset of study sites. This approach ensured that an expert's sites were spatially and compositionally diverse in multivariate space.

The survey presented sites in random order one by one, and experts were asked to estimate the probability of occurrence for each of their selected target species during the breeding season at each site. Experts could complete less than 30 sites (e.g., skipping sites in which they were unfamiliar) and could elect to complete an additional 30 sites. Site-specific covariate data (Appendix A.1) were displayed in a window containing an interactive satellite image, pie charts depicting land cover, forest species and forest age composition, and a list of relevant site characteristics (Fig. 2.2). The interactive satellite image (Google Map, Google, Inc., Mountain View, California USA) was featured in the left portion of the browser window with an imbedded boundary circle to indicate the survey site location and extent (Fig. 2.2A). Experts could adjust the view of the satellite image (e.g., zoom or drag) to aid in site evaluation. Above the map image were two tabs (“Land Cover” and “Forest Composition”; Fig. 2.2B) that experts could select to view pie charts with percent cover information for site variables. An additional table of site characteristics related to climate, topography/geography, and road cover was displayed below the satellite image (Fig. 2.2C). The right portion of the browser window displayed an output graph of the expert’s response (Fig. 2.2D). The title of this graph included the expert’s target species, with the active selection designated by bolded text. Below the graph were two sliding scale bars (“Probability of Occurrence” and “Confidence in this Estimate”) that experts were able to manipulate to provide an estimate of species occurrence within the site.

Experts were asked to estimate occurrence on a probability scale ranging from “low” (0 probability of occurrence or absent) to “high” (equal to a probability of 1.0, or 100%), and then indicate their confidence in each estimate on a scale from “low” (confidence value of 0) to “high” (confidence value of 1.0). Confidence measures were used to generate what the experts believed was the “true range” of probability of occurrence (e.g., an estimate with low confidence would have a large range of possible values). The manipulation of these estimate measures instantaneously altered the output graph, providing experts with visual feedback of their estimations.

Section 3. This section involved a covariate importance ranking exercise and a brief post survey questionnaire. Experts were able to define additional variables they believed influence species distribution; these variables were combined with the covariates presented in the site surveys during model development. Experts then allocated directionality (positive, negative, or neutral) to each variable and ranked them in their perceived order of importance (Appendix A.2). The post survey questionnaire collected information about the survey experience and allowed experts to provide feedback on the elicitation process (Appendix B.2).

Objective 3 – Develop species distribution models

Data. Expert survey responses were downloaded into a comprehensive dataset that provided expert opinion data in the form of occurrence probabilities and measures of uncertainty (ranging from 0 to 1), as well as site data and site-specific covariate information. The dataset contained site level information for 74 different covariates; these covariates included the site variables used in the elicitation survey (n = 54; Appendix A.1); however, additional expert-identified variables (n = 6), forest classification variables (n = 9), and climate variables (n = 5) were also included, as described later.

Model Covariate Reduction. For each species, the full covariate list was reduced to a "working" covariate list by three criteria: 1) Variables from the comprehensive list that demonstrated a strong linear correlation ($r \geq 0.6$) with the probability of occurrence data were included in the species' working covariate list; 2) The top ranked variables identified in the survey's covariate ranking exercise were included in the working covariate list. An importance score was calculated for each of the top ranked variables (i.e., variables ranked 1-5) by dividing the variables average rank by the number of times the variable appeared in the top five. Variables with an importance score less than or equal to 1 were identified as expert covariates and were included in the working covariate list; and 3) Any variables that were not specified by covariate rank or expert response criteria, yet were commonly identified in the literature, were also included in the working covariate list. Ultimately, the “working” covariate list was reduced to a simplified “final” covariate set (Table 2.2) to be used in species-specific distribution modeling.

We considered each variable in the working list at two spatial scales: A uniform site scale (1-km radius) was used for all species as well as a secondary species-specific landscape scale, which roughly corresponded to the species’ home range size (500-m, 3-km, or 5-km radius; Table 2.1). Scaled working covariates were compared using single variable models; the better performing scale for each variable was retained in the working list. Finally, we examined correlations within the working covariate list to eliminate redundant variables, providing a “final” covariate set for species-specific distribution modeling. Variables that did not exhibit correlation were retained in the final covariate list. Variables that exhibited correlation were compared using preliminary single variable models. Within a correlated set, only the top performing variable was retained, and the remaining variables were removed from the covariate list.

Model Selection. We used generalized linear mixed modeling approaches to develop SDMs from expert elicited probability of occurrence data. Species-specific models were analyzed in the R package lme4 (Bates, Mächler, Bolker, & Walker, 2014) with stepwise modeling methods (described below). We used a glmer weighted approach (from the lmer4 package) to weight each expert’s occurrence estimate by the expert’s corresponding confidence estimate at a given site. This allowed us to account for expert identified uncertainty during model selection, giving higher influence to site elicitations in which experts were confident and lower influence to potentially less accurate estimates. For all models the response variable was probability of occurrence; expert, site, eco-region and state terms were specified as random-effects and covariates from the species' final covariate list were considered fixed-effects. Null models only contained random-effect variables for site and expert (these random-effects were included in all models).

Our stepwise model development incorporated forward and backward model selection and tested every variable combination to determine the best-fit model. Beginning with forward selection, a species' null model was run with glmer (from the lmer4 package) to create a logistic start model, and covariates were added sequentially based on the model's p-value criterion (0.05). Backward selection followed a similar approach with the glmer function (lmer4 package), beginning with the comprehensive model and dropping covariates from the model during each step of selection based on the p-value. To ensure that the best combination of variables was identified during stepwise selection, a secondary check was run to test all combinations of the variables retained during forward and backward selection. All combination models were ranked according to Akaike's Information Criterion (AIC; Burnham and Anderson 2002) and the top performing model was selected. The top performing variable combination – typically consistent with the model identified by forward and backward selection – represented the final "best-fit" model.

Model Validation. We used research grade species occurrence data (presence-only) from the crowdsourced biodiversity application, iNaturalist (iNaturalist, 2019) to test the performance of each species' top ranked model. For each species, we extracted occurrence data for sightings reported in the New England region between 2010 and 2018 (breeding season only). We trimmed datasets to help ensure that records were both confirmed (i.e., records included photo or audio evidence and an accurate species identification) and unique observations (i.e., records were distinct through time and space; Table 2.1). To test model performance, sighting (i.e., presence) locations were buffered (100-m radius) and then superimposed on the species regional distribution map. Model estimated occurrence was calculated for each iNaturalist sighting. Predicted occurrences were then binned from 0 to 1 in increments of 0.1, and then plotted in a histogram to display how well the model predicted occurrence at these sites. Histograms that were skewed to the right (toward 1) indicated that the model estimated high occurrence likelihoods for many of the iNaturalist sites, suggesting that the model performed well against empirical data.

Objective 4 – Map species distributions

Mapping. We developed distribution maps for each species across New England using the raster package in R (Hijmans, 2016). For each species, we multiplied the parameter coefficients from the top model to each corresponding covariate value in a given cell (30 x 30 m) in raster maps of the study area. These values were then summed to obtain a logit score for each cell. Any SDM with significant random-effects (such as state or ecoregion random-effects) were added at this time. Logits were then transformed to occurrence probabilities with the logit link function. This process generated a set of spatially uniform maps that depicted the distributions of focal species throughout the New England region. The resulting distribution maps were also stacked and then cell values summed across all species to create an aggregate occurrence map. This community-aggregated map provided a measure of species richness for the focal group

(Sauer, Blank, Zipkin, Fallon, & Fallon, 2013). Richness values potentially ranged from 0 (no species present) to 10 (all species present).

2.4. Results

Objectives 1 & 2 – Multispecies expert opinion survey

A total of 46 wildlife experts participated in the New England Wildlife Survey and completed surveys from August to November 2017. Expert participants were primarily scientists, state agency personnel, and hunters/trappers. Experts contributed to site surveys in Connecticut (n = 4), Maine (n = 11), Massachusetts (n = 6), New Hampshire (n = 20), Rhode Island (n = 4), and Vermont (n = 25). A total of 3,396 occurrence estimates were collected at 1,258 different survey sites. Occurrence estimates were collected for American black bear (n = 423), bobcat (n = 373), coyote (n = 355), gray fox (n = 188), moose (n = 459), raccoon (n = 233), red fox (n = 253), striped skunk (n = 198), white-tailed deer (n = 535) and wild turkey (n = 379; Table 2.1).

Objective 3 – Species distribution models

Species-specific "final" covariate lists contained between six and thirteen probable drivers of distribution (Tables 2.2 and 2.3). The final lists contained variables identified by expert opinion, literature review and correlation with species occurrence, and were specified as fixed-effects during species distribution modeling. Random-effects for state and eco-region were included in 4 of 10 SDMs (Table 2.4) and shifted the model intercept within the corresponding regions (Table 2.5). Proportion agriculture was included in the majority (7 of 10) of the SDMs; forest variables were included in 9 of 10 SDMs, and climate variables were included in 6 of 10 SDMs.

Across species, top-ranking models contained two to six fixed-effect covariates and two or three random-effect covariates (Table 2.4). All fixed-effect model covariates exhibited individual effects significantly different from zero (Table 2.5, Appendix A.3). All models had normally distributed residuals (mean = 0), and adhered to the assumptions of probabilistic likelihood models (Appendix A.4).

Final SDMs converged and performed well when tested against crowdsourced empirical data. Seven of the 10 SDMs estimated high occurrence probabilities (mean ≥ 0.6) for greater than 75% of the iNaturalist sites (Fig. 2.3). Two of the remaining SDMs performed with moderate success – i.e., high occurrence probabilities were estimated for 67% (bobcat) and 65% (wild turkey) of the iNaturalist sites. One species' model (gray fox) exhibited low performance – i.e., high occurrence probabilities were estimated at only 33% of the iNaturalist sites.

Objective 4 – Species distribution maps

Distribution maps provided fine scale species-specific probability of occurrence estimates throughout New England (Fig. 2.4). ***American black bear*** occurrence was relatively high (average probability of occurrence, μ_p = 0.80; Table 2.6), with greatest occurrence likelihoods in central regions of Vermont, New Hampshire, and Maine (Fig. 2.4A). ***Bobcat*** occurrence likelihoods were moderate throughout New England (μ_p = 0.67; Table 2.6), with higher likelihoods in the less developed northern regions (Fig. 2.4B). ***Coyote*** occurrence was high throughout the region (μ_p = 0.92; Table 2.6), with lower probability of occurrence in the highly developed regions of Massachusetts, Rhode Island, and Connecticut (Fig. 2.4C). ***Gray Fox*** occurrence was low throughout New England (μ_p = 0.42; Table 2.6), with moderate occurrence likelihoods in central regions of Vermont and New Hampshire (Fig. 2.4D), and distinctly higher mean occurrence observed in the less developed western regions of Massachusetts ($\mu_{p\ Massachusetts} = 0.69$; Table 2.6). ***Moose*** occurrence varied considerably between northern and southern New England (Fig. 2.4E), leading to moderate regional occurrence ($\mu_p = 0.52$; Table 2.6). ***Raccoon*** occurrence was high throughout much of New England ($\mu_p = 0.87$; Table 2.6), with lower occurrence probabilities moving north into the mountainous regions of Vermont, New Hampshire, and Maine (Fig. 2.4F). ***Red Fox*** occurrence was moderate throughout the region (μ_p p = 0.64; Table 2.6), with highest likelihoods in regions of northwestern Vermont and northeastern Maine (Fig. 2.4G). ***Striped skunk*** occurrence was moderate-high throughout much of New England ($\mu_p = 0.75$; Table 2.6), with higher likelihoods in the southern states and lower elevation regions of Vermont, New Hampshire, and Maine (Fig. 2.4H). ***White-tailed deer*** occurrence was high throughout the region ($\mu_p = 0.89$; Table 2.6), except in the highly developed areas of Massachusetts, Rhode Island and Connecticut (Fig. 2.4I). ***Wild turkey*** occurrence was moderate throughout much of the region ($\mu_p = 0.68$; Table 2.6) with highest occurrence likelihoods in the less developed areas of Connecticut, Vermont, Rhode Island, and Massachusetts (Fig. 2.4J).

Overall, 5 focal species (American black bear, coyote, raccoon, striped skunk, and white-tailed deer) exhibited high regional occurrence ($\mu_p > 0.75$), 4 species (bobcat, moose, red fox, and wild turkey) exhibited moderately high regional occurrence ($0.50 < \mu_p \leq 0.75$) and 1 species (gray fox) exhibited moderately low regional occurrence ($0.25 < \mu_p \leq 0.50$). State-based statistics for each species show considerable variability in occurrence likelihoods across state-boundaries (Table 2.6).

Species richness estimates (s) ranged from 2.42 to 8.72, with a regional average of 7.16 (Fig. 2.5, Table 2.7). Occurrence across all species was highest in the lower elevation regions of Maine, New Hampshire, and Vermont, and lowest in the most developed regions of Massachusetts, Connecticut, and Rhode Island. The largest connected area with high focal species richness ($s \geq 8.0$) was along the Connecticut River Valley in northern Massachusetts through Vermont and New Hampshire and north into the Western Foothills of Maine. At the state level, focal species richness was highest in Vermont (average species richness, $\mu_s = 7.47$) and Maine ($\mu_s = 7.32$) and lowest in Rhode Island ($\mu_s = 6.13$) and Massachusetts ($\mu_s = 6.61$; Table 2.7).

2.5. Discussion

Species distribution models capture the influence of landscape conditions on wildlife occurrence and can help inform and prioritize conservation and management activities (Elith & Leathwick, 2009). We demonstrated that expert elicitation techniques combined with stepwise mixed-effect modeling methods can be used to develop spatially compatible SDMs for wildlife species. Our SDMs for 10 harvested species performed well at predicting species occurrence throughout the New England region, offering new information on factors that shape distributions. This set of spatially compatible and regionally applicable models offer probabilistic insight that can help inform conservation and management decisions.

Expert Elicitation. Expert elicitation is used in many fields to gain information when empirical data are limited, unavailable, or difficult to obtain (James et al., 2010). To overcome the limitations and challenges of observational studies, expert opinion data have been used by numerous studies to model habitat quality and predict wildlife distributions (Aylward et al. 2018; Murray et al. 2009; Pearce et al. 2001; Yamada et al. 2003), identify habitat linkages (Clevenger et al., 2002), and estimate species movement corridors (Aylward et al., 2018). Elicitation offers a relatively quick and inexpensive approach to data collection that can be particularly valuable to large-scale studies of rare or poorly documented species. Collecting an ample amount of occurrence data for 10 different wildlife species at the New England regional extent would be difficult and costly without the use of expert elicitation techniques.

While expert elicitation generates valuable information and overcomes many challenges of observational studies, opinion-based studies introduce their own challenges. Using opinion-based data can create room for personal biases, and the possible introduction of inaccurate information (Low Choy, O'Leary, & Mengersen, 2009). Additionally, if an elicitation platform is challenging to use, difficult to understand, or provides ambiguous instructions, experts may misinterpret how best to provide opinions, which could lead to low quality data (James et al., 2010; Low Choy et al., 2009). We addressed these concerns by designing a survey application that was user-friendly, provided clear and concise instructions, and offered an engaging and interactive experience (https://code.usgs.gov/vtcfwru/amsurvey/wiki). The survey was tested on several volunteers beforehand to ensure ease of use and clarity. We also recruited a large cohort (n = 46) of experts from management agencies and research institutions throughout New England, and had experts provide responses only for the species and regions in which they had self-identified expertise. Contribution from numerous wildlife experts helped to reduce individual bias and collect regionally representative data.

We developed models of distribution during the breeding season, which is often the focus of species and population level management. However, because the actual timing of the breeding season varied among species in the focal group, the seasonal accuracy of expert's responses may have diminished when experts provided feedback for multiple species. This could have led to more generalized occurrence data and may explain why variables in some of the SDMs were not breeding season specific (e.g., the inclusion of grassland in the wild turkey model). Expert elicitation modeling could be improved by reducing seasonal ambiguity (e.g., survey species with a common breeding season) or conducting more specific assessments (e.g., survey a single species).

There are also several potential benefits of using expert elicitation to create SDMs. First, the approach incorporates information from expert knowledge and experience, as well as the literature. The elicitation process required experts to assign occurrence probabilities along with their certainty, effectively aggregating the expert's opinion as an informed prior probability distribution for each site. In setting this distribution, experts are using knowledge of the species, which is presumably based on an amalgamation of their experiences with the species and the landscape. These educated responses provide a level of information not necessarily obtainable from an empirical study (Kynn, 2005; Justine V. Murray et al., 2009). Second, including experts in data collection may promote expert buy-in and user confidence in the data and resulting products (i.e., maps), potentially leading to more proactive and collaborative conservation and management decisions (Reed, 2008). Third, the trends observed in our SDMs were consistent with the literature and provide covariate effect sizes that allowed us to estimate species occurrence throughout the study region.

SDM Performance. We validated our models with observational data (presence records) from the crowd-source platform, iNaturalist. While other sources of data were available for some of our focal species such as radio-collar and harvest data, these records were often concentrated at small spatial scales or lacked a reasonable spatial resolution (e.g., harvest locations recorded at the town or wildlife management unit scale), were inconsistent across space and time, or were collected in time periods that did not coincide with our landcover data. We used iNaturalist data because they provided a consistent source of region-wide occurrence data for all 10 focal species. The iNaturalist records were validated and classified as 'research grade', and allowed us to test model performance with separate data, obtained through alternative methods – i.e., community observation rather than expert opinion.

Our SDMs generally fit the iNaturalist data well, suggesting that they reflected the effects of landscape conditions on occurrence for all species in the focal group, except one, the gray fox. There are several possible explanations for the lower performance of the gray fox model, including: 1) the sample size of expert opinion values may not have been adequate enough to describe occurrence (samples size for this species was considerably less than for other species; Table 2.1); 2) experts may have had less certainty about estimating occurrence for the species, which is poorly studied in the region; and 3) the available validation data may have been biased and less representative for the species. Using community-sourced occurrence data for validation purposes presents challenges (Sardà-Palomera et al., 2012; Tulloch & Szabo, 2012). While measures were taken to reduce bias and maximize data accuracy, community-sourced data is inherently skewed towards areas most accessible to the human observer (i.e., developed and/or open land types) and is restricted by the voluntary nature in which it is collected (Tulloch, Mustin, Possingham, Szabo, & Wilson, 2013; Tulloch & Szabo, 2012). Testing the gray fox model against other independent data sets would help assess the accuracy of the model. Despite the challenges of model development and validation, our SDMs provide novel information about the effect size of important variables and can be used to estimate species occurrence in new locations or changing landscapes.

Distribution Models and Maps. Many studies have been conducted to identify important habitats for wildlife species. However, few studies have quantified the effects that habitat variables have on multiple wildlife species or large regional extents. Our approach generated accessible expert informed models for multiple wildlife species, allowing us to determine species-specific effects and compare effects across species in the focal group. Generally, most SDMs included variables at both site scale and the species-specific landscape scale, emphasizing the importance of assessing variables at multiple spatial scales as certain variables may be more or less influential at different scales.

Focal species occurrence was generally highest in structurally diverse forested areas and lowest in highly developed areas. These relationships are not surprising as many of the focal species are forest obligates. All SDMs included at least one forest variable. The two forest variables that appeared in SDMs most commonly were mature forest and forest edge; however, six other forest composition and forest structure variables appeared across all SDMs. The inclusion of these forest variables emphasizes the importance of habitat structure and habitat configuration for the wildlife species we included in the study, and the need to effectively conserve forested lands in the face of human development and land-use change. Because forest use activities can alter these variables on the ground, it is important to have models (and maps) that capture the influence of any changes and can be continually improved or updated as new information becomes available (i.e., forming the basis of adaptive management; Williams, 2011).

Observing lower occurrence probabilities in developed areas is also not surprising. While many species utilize urbanized landscapes, the presence of development often reduces the availability and accessibility of important habitat (Fischer & Lindenmayer, 2007). We found that high disturbance development variables, including roads and developed areas, exhibited negative relationships with occurrence in six of the SDMs. However, human-associated variables such as forest edge and agriculture appeared in eight of our SDMs and exhibited positive relationships with occurrence. These differences indicate that varied levels of human disturbance impact wildlife in different ways and suggest that certain levels of anthropogenic influence can produce favorable habitat conditions within a landscape (Fahrig et al., 2011; Hunter & Schmiegelow, 2011; Tews et al., 2004).

We were also able to quantify relationships between climate variables and species occurrence. Three species models (American black bear, moose, and red fox) included climate variables as fixed-effects. Isolating climate variables as direct influencers of distribution can provide insight on how shifts in climate directly impact wildlife species. While several studies have identified climate change as a threat to wildlife (Chapin et al., 2000; Pacifici et al., 2017; Thomas et al., 2004), little is known about the effects of climate variables on individual species. Our modeling approach allowed us to quantify relationships between species occurrence and important climate variables, offering a quantitative basis for assessing the consequences of climate and land-use change. This information may be particularly important as changes in climate and land-use are projected to increase in the future and will likely have considerable impacts on species distributions and overall species richness (Chapin et al., 2000; Díaz et al., 2019; Rustad et al., 2012).

Through expert elicitation and mixed modeling methods, we were able to develop a collection of SDMs and distribution maps that offer valuable information about wildlife occurrence in New England. These versatile modeling tools provide regionally applicable and spatially compatible information for multiple wildlife species and provide a means for future scenario-based assessments. These forecasted assessments can help inform proactive decision-making and benefit long-term management and conservation planning throughout the New England region.

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2.8. Tables

Table 2.1. List of wildlife species in the New England region of the northeastern United States included in expert elicitation and model development. Sample size ranged between 188 and 535 and indicates the number of occurrence estimates collected for each species through an expert elicitation survey. Species models were validated using iNaturalist datasets that included between 106 and 1,771 occurrence records. Generalized home range scales (500m, 3km, and 5km) indicate the secondary analysis scale(s) used for each species during model development.

Common name	**Genus**	**Species**	**Sample size**	**Home range scale**	**iNaturalist sample size**
American black bear	*Ursus*	*americanus*	423	5km	249
Bobcat	*Lynx*	*rufus*	373	3km	424
Coyote	*Canis*	*latrans*	355	3km	338
Gray fox	*Urocyon*	*cinereoargenteus*	188	3km	106
Moose	*Alces*	*alces*	459	5km	280
Raccoon	*Procyon*	*lotor*	233	500m	556
Red fox	*Vulpes*	*vulpes*	253	3km	443
Striped skunk	*Mephitis*	*mephitis*	198	500m	193
White-tailed deer	*Odocoileus*	*virginianus*	535	3km	1771
Wild turkey	*Meleagris*	*gallopavo*	379	500m, 3km	1652

Table 2.2. Final covariates used in step-wise model selection for each species. Each species' covariate list was simplified from 74 variables assessed at the standard site scale (1k) and a species-specific landscape scale (500m, 3k, or 5k). Standardized step-based methods were used to identify the 6 to 13 most influential (scaled) variables believed to impact species occurrence throughout the New England region.

Covariates	**Species (scale)**									
	American black bear	Bobcat	Coyote	Gray fox	Moose	Raccoon	Red fox	Striped skunk	White-tailed deer	Wild turkey
mean_annual_precip_mm	5k	-	-	-	-	-	-	-	-	-
mean_DEM_km	-	-	-	1k	-	500m	-	500m	-	-
mean_fall_tmax_degC	-	-	-	-	1k	-	-	-	-	-
mean_winter_precip_mm	-	3k	1k	-	-	-	3k	-	3k	-
prop_agriculture	5k	1k	-	3k	-	500m	1k	500m	1k	-
prop_all_roads	1k	-	-	-	-	-	-	-	-	-
prop_conif_forest	-	-	-	-	5k	-	3k	-	3k	-
prop_decid_forest	-	-	-	-	-	500m	-	-	-	1k
prop_developed	-	1k	-	-	1k	500m	-	-	-	-
prop_early_succession	1k	3k	-	-	5k	-	3k	-	3k	3k
prop_fagugran	5k	-	-	-	-	-	-	-	3k	1k
prop_forest	5k	-	-	-	5k	-	3k	-	-	-
prop_forest_edge	-	1k	1k	1k	-	-	-	500m	-	1k
prop_grassland	-	-	1k	-	-	-	-	500m	-	3k
prop_hemlock_tamarack_cedar	-	-	-	-	-	-	-	-	3k	-
prop_high_dev	-	-	-	-	-	-	1k	-	1k	500m
prop_major_roads	-	-	3k	-	-	-	-	-	-	-
prop_mature_forest	1k	-	-	-	-	500m	-	500m	1k	500m
prop_oak	5k	-	-	-	-	500m	-	500m	-	3k
prop_old_forest	-	-	-	-	-	-	-	-	-	3k
prop_riparian	-	-	-	1k	5k	1k	3k	-	1k	1k
prop_rock	-	-	-	-	-	-	-	500m	-	-
prop_shrubland	-	3k	3k	3k	1k	500m	3k	1k	3k	3k
prop_waterbodies	-	-	1k	-	-	1k	-	-	-	-
prop_wetland	5k	-	3k	-	-	-	-	1k	-	-
prop_young_forest	-	-	-	1k	1k	-	1k	-	3k	3k

Table 2.3. Covariates used in model development for 10 wildlife species in the New England region of the northeastern United States. A total of 26 fixed-effect variables and 4 random-effect variables were included in model development. The fixed-effects included 22 land cover variables, 1 topographic variable, and 3 climate variables. The random-effects included 2 variables (site and expert) that were included in all models and 2 candidate variables (state and eco-region). Fixed-effect variables were included at the site scale (1k) or a generalized home range scale (500m, 3k, or 5k).

Variable	Covariate name	Description	Source
Agriculture	prop_agriculture	Area where land cover is classified as pasture, hay and cultivated crops.	National Land Cover Database 2011 (NLCD 2011)
All Roads	prop_all_roads	Area where land cover is classified as major roads (controlled access highways, secondary highways or major connecting roads, ramps) or local roads (local roads, 4WD roads, private driveways).	National Transportation Database (NTD 2016)
American Beech	prop_fagugran	Forested land that is occupied by American Beech (*Fagus grandifolia*).	Duveneck et al. 2015
Annual Precipitation	mean_annual_precip_mm	Average annual precipitation during the years 2010, 2011 and 2012.	Duveneck and Thompson, 2017; Stoner et al., 2013
Barren Land	prop_rock	Area where land cover is classified as barren land (i.e. rock, sand, or clay).	NLCD 2011
Conifer Forest	prop_conif_forest	Area where land cover is classified as evergreen forest.	NLCD 2011
Deciduous Forest	prop_decid_forest	Area where land cover is classified as deciduous forest.	NLCD 2011
Developed	prop_developed	Area where land cover is classified as developed open space, low intensity, medium intensity and high intensity development.	NLCD 2011
Early Successional Forest	prop_early_succession	Forested land that is classified by tree cohorts between 2 and 19 years old.	Duveneck & Thompson 2017
Eco-Region	EcoRegion	Area classified by terrestrial Eco Regions.	The Nature Conservancy 2009
Elevation	mean_DEM_km	Height above sea level in kilometers.	Digital Elevation Model (DEM 2017)
Fall: Average Daily High Temperature	mean_fall_tmax_degC	Average daily high temperature observed during the months of September, October and November during 2010-2012.	Duveneck & Thompson 2017; Stoner et al. 2013
Forest	prop_forest	Area where land cover is classified as deciduous, evergreen & mixed forest.	NLCD 2011
Forest Edge	prop_forest_edge	Area classified as forest that is within 300m of non-forest land cover.	NLCD 2011
Grassland	prop_grassland	Area where land cover is classified as grassland, herbaceous, pasture or hay.	NLCD 2011
Hemlock-Tamarack-Cedar Forest	prop_hemlock_tamarack_cedar	Forested land where AGB (above ground biomass) is dominated by Eastern Hemlock (*Tsuga canadensis*), native Tamarak (*Larix laricina*) and Northern White Cedar (*Thuja occidentalis*).	Duveneck & Thompson 2017
High Development	prop_high_dev	Area where land cover is classified as medium or high intensity development.	NLCD 2011
Late Successional Forest	prop_old_forest	Forested land that is classified by tree cohorts older than 100 years.	Duveneck & Thompson 2017
Major Roads	prop_major_roads	Area where land cover is classified as a major road (i.e. controlled access highways, secondary highways or major connecting roads, ramps).	NTD 2016
Mature Forest	prop_mature_forest	Forested land that is classified by tree cohorts between 40 and 100 years old.	Duveneck & Thompson 2017
Oak Forest	prop_oak	Forested land where AGB is dominated by White Oak (*Quercus alba*), Scarlet Oak (*Quercus coccinea*), Chestnut Oak (*Quercus prinus*), Northern Red Oak (*Quercus rubra*) and Black Oak (*Quercus velutina*).	Duveneck & Thompson 2017
Riparian	prop_riparian	Area where vegetation is classified as riparian.	LANDFIRE 2012
Shrubland	prop_shrubland	Area where land cover is classified as shrub/scrub.	NLCD 2011
State	State	Area classified by USA state boundaries.	MassGIS, 2018
Total Winter Precipitation	mean_winter_precip_mm	Average cumulative winter (December - February) precipitation during the years 2010-2012. Note: This measure includes all types of precipitation, not just snowfall.	Duveneck & Thompson 2017; Stoner et al. 2013
Water	prop_waterbodies	Area occupied by waterbodies; lakes, ponds, reservoirs, estuaries, swamps and marshes.	NLCD 2011
Wetland	prop_wetland	Area classified as woody wetlands or emergent herbaceous wetlands.	NLCD 2011
Young Forest	prop_young_forest	Forested land that is classified by tree cohorts between 20 and 39 years old.	Duveneck & Thompson 2017

Table 2.4. Final distribution models for estimating species occurrence throughout the New England region of the northeastern United States. Models were developed using expert-opinion data and generalized linear mixed modeling. Expert and site specific random-effects and fixed effects were included during model fitting.

<table>
<tr><th>Species</th><th>Model formula</th></tr>
<tr><td>American black bear</td><td>Mean ~ prop_mature_forest + prop_all_roads + prop_forest_5k + mean_annual_precip_mm_5k + prop_fagugran_5k + (1 | State) + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Bobcat</td><td>Mean ~ prop_developed + prop_forest_edge + prop_agriculture + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Coyote</td><td>Mean ~ prop_waterbodies + prop_forest_edge + prop_major_roads_3k + prop_wetland_3k + prop_agriculture + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Gray fox</td><td>Mean ~ prop_forest_edge + prop_agriculture_3k + mean_DEM_km + (1 | State) + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Moose</td><td>Mean ~ prop_young_forest + prop_developed + prop_shrubland + mean_fall_tmax_degC + prop_forest_5k + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Raccoon</td><td>Mean ~ prop_agriculture_500m + prop_mature_forest_500m + mean_DEM_km_500m + prop_oak_500m + prop_developed_500m + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Red fox</td><td>Mean ~ prop_agriculture + prop_high_dev + mean_winter_precip_mm_3k + prop_shrubland_3k + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Striped skunk</td><td>Mean ~ mean_DEM_km_500m + prop_mature_forest_500m + prop_agriculture_500m + prop_forest_edge_500m + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>White-tailed deer</td><td>Mean ~ prop_agriculture + prop_high_dev + prop_mature_forest + prop_hemlock_tamarack_cedar_3k + (1 | EcoRegion) + (1 | Expert) + (1 | Site)</td></tr>
<tr><td>Wild turkey</td><td>Mean ~ prop_decid_forest + prop_forest_edge + prop_riparian + prop_grassland_3k + (1 | EcoRegion) + (1 | Expert) + (1 | Site)</td></tr>
</table>

Table 2.5. Fixed-effect parameter estimates with standard error, upper and lower 95% confidence intervals (CI), and p-values for covariates in 10 species models. Random-effects associated with state or eco-region are included when significant, noted in parentheses. Models estimate species-specific occurrence in the New England region of the northeastern United States.

Species	Covariate	Estimate	Standard error	Lower CI	Upper CI	P-value
American black bear	(Intercept)	25.64	11.34	3.42	47.86	0.0237
	prop_mature_forest	3.27	0.86	1.59	4.95	0.0001
	prop_all_roads	-12.47	2.15	-16.68	-8.26	0.0000
	prop_forest_5k	6.16	0.88	4.43	7.90	0.0000
	mean_annual_precip_mm_5k	-21.90	8.50	-38.57	-5.24	0.0100
	prop_fagugran_5k	2.40	1.01	0.42	4.38	0.0174
	(Connecticut)	1.90	-	-	-	-
	(Maine)	0.48	-	-	-	-
	(Massachusetts)	-0.44	-	-	-	-
	(New Hampshire)	-0.77	-	-	-	-
	(Rhode Island)	0.14	-	-	-	-
	(Vermont)	-1.41	-	-	-	-
Bobcat	(Intercept)	0.22	0.36	-0.48	0.93	0.5322
	prop_developed	-2.6	0.50	-3.58	-1.62	0.0000
	prop_forest_edge	1.02	0.42	0.19	1.85	0.0155
	prop_agriculture	1.42	0.52	0.40	2.44	0.0064
Coyote	(Intercept)	1.42	0.72	0.01	2.82	0.0481
	prop_waterbodies	-4.08	0.97	-5.99	-2.18	0.0000
	prop_forest_edge	2.79	0.54	1.73	3.86	0.0000
	prop_major_roads_3k	-32.05	9.94	-51.54	-12.56	0.0013
	prop_wetland_3k	2.85	1.34	0.21	5.48	0.0341
	prop_agriculture	1.31	0.71	-0.07	2.70	0.0636
Gray fox	(Intercept)	-3.53	0.76	-5.02	-2.03	0.0000
	prop_forest_edge	5.57	0.74	4.12	7.02	0.0000
	prop_agriculture_3k	3.31	1.15	1.06	5.56	0.0039
	mean_DEM_km	-1.82	0.89	-3.57	-0.08	0.0408
	(Connecticut)	-0.84	-	-	-	-
	(Maine)	-0.80	-	-	-	-
	(Massachusetts)	1.99	-	-	-	-
	(New Hampshire)	-0.29	-	-	-	-
	(Rhode Island)	0.16	-	-	-	-
	(Vermont)	0.49	-	-	-	-
Moose	(Intercept)	8.13	1.61	4.97	11.29	0.0000
	prop_young_forest	7.02	2.93	1.27	12.76	0.0167
	prop_developed	-4.59	0.78	-6.11	-3.06	0.0000
	prop_shrubland	5.11	1.37	2.43	7.79	0.0002
	mean_fall_tmax_degC	-73.71	8.98	-91.32	-56.1	0.0000
	prop_forest_5k	3.52	0.65	2.25	4.79	0.0000
Raccoon	(Intercept)	1.65	0.71	0.27	3.04	0.0194
	prop_agriculture_500m	3.04	0.75	1.58	4.51	0.0000
	prop_mature_forest_500m	1.21	0.54	0.15	2.27	0.0248
	mean_DEM_km_500m	-2.09	0.66	-3.37	-0.80	0.0015
	prop_oak_500m	1.66	0.83	0.03	3.3	0.0466
	prop_developed_500m	2.26	0.60	1.07	3.44	0.0002
Red fox	(Intercept)	-3.16	1.77	-6.63	0.3	0.0735
	prop_agriculture	3.28	0.61	2.09	4.47	0.0000
	prop_high_dev	-3.23	1.21	-5.60	-0.86	0.0076
	mean_winter_precip_mm_3k	12.65	6.30	0.31	24.99	0.0445
	prop_shrubland_3k	3.50	2.10	-0.63	7.62	0.0966
Striped skunk	(Intercept)	1.91	0.79	0.36	3.45	0.0158

	mean_DEM_km_500m	-6.25	0.60	-7.44	-5.07	0.0000
	prop_mature_forest_500m	0.91	0.58	-0.23	2.06	0.1182
	prop_agriculture_500m	3.40	0.76	1.91	4.88	0.0000
	prop_forest_edge_500m	0.74	0.49	-0.22	1.70	0.1288
White-tailed deer	(Intercept)	1.17	0.68	-0.17	2.50	0.0872
	prop_agriculture	4.22	0.83	2.60	5.84	0.0000
	prop_high_dev	-10.52	0.84	-12.17	-8.88	0.0000
	prop_mature_forest	1.47	0.62	0.27	2.68	0.0168
	prop_hemlock_tamarack_cedar_3k	10.50	1.69	7.18	13.82	0.0000
	(Lower New England / Northern Piedmont)	0.33	-	-	-	-
	(North Atlantic Coast)	0.06	-	-	-	-
	(Northern Appalachian / Acadian)	-0.09	-	-	-	-
	(St. Lawrence - Champlain Valley)	-0.41	-	-	-	-
Wild turkey	(Intercept)	-1.83	0.69	-3.18	-0.48	0.0080
	prop_decid_forest	1.33	0.58	0.20	2.47	0.0214
	prop_forest_edge	1.95	0.59	0.81	3.10	0.0008
	prop_riparian	2.97	1.17	0.67	5.26	0.0112
	prop_grassland_3k	16.76	2.52	11.81	21.70	0.0000
	(Lower New England / Northern Piedmont)	0.35	-	-	-	-
	(North Atlantic Coast)	0.82	-	-	-	-
	(Northern Appalachian / Acadian)	-0.05	-	-	-	-
	(St. Lawrence - Champlain Valley)	-1.49	-	-	-	-

Table 2.6. Regional and state-level mean occurrence estimates for 10 wildlife species in the New England region of the northeastern United States. Occurrence estimates were based on species-specific distribution models fit using expert-opinion data and generalized linear mixed modeling. Species models incorporated site and expert associated random intercept effects and fixed habitat effects.

Species	Region	Minimum	Maximum	Mean	Standard Deviation
American black bear	Connecticut	0.00	1.00	0.73	0.31
	Maine	0.00	1.00	0.91	0.15
	Massachusetts	0.00	1.00	0.46	0.37
	New Hampshire	0.00	1.00	0.84	0.23
	Rhode Island	0.00	0.97	0.42	0.32
	Vermont	0.00	1.00	0.74	0.31
	New England	0.00	1.00	0.80	0.29
Bobcat	Connecticut	0.09	0.81	0.57	0.20
	Maine	0.09	0.84	0.70	0.07
	Massachusetts	0.09	0.80	0.55	0.20
	New Hampshire	0.09	0.80	0.69	0.11
	Rhode Island	0.09	0.77	0.52	0.21
	Vermont	0.09	0.84	0.72	0.07
	New England	0.09	0.84	0.67	0.13
Coyote	Connecticut	0.07	0.99	0.89	0.13
	Maine	0.03	0.99	0.94	0.13
	Massachusetts	0.02	0.99	0.87	0.16
	New Hampshire	0.04	0.99	0.94	0.11
	Rhode Island	0.03	0.99	0.83	0.20
	Vermont	0.04	0.99	0.93	0.14
	New England	0.02	1.00	0.92	0.14
Gray fox	Connecticut	0.01	0.81	0.27	0.17
	Maine	0.00	0.82	0.31	0.16
	Massachusetts	0.12	0.99	0.69	0.25
	New Hampshire	0.00	0.87	0.45	0.18
	Rhode Island	0.03	0.88	0.36	0.25
	Vermont	0.01	0.98	0.61	0.20
	New England	0.00	0.99	0.42	0.24
Moose	Connecticut	0.00	0.80	0.09	0.09
	Maine	0.00	1.00	0.67	0.28
	Massachusetts	0.00	0.87	0.15	0.18
	New Hampshire	0.00	1.00	0.54	0.30
	Rhode Island	0.00	0.66	0.06	0.08
	Vermont	0.00	1.00	0.59	0.27
	New England	0.00	1.00	0.52	0.34
Raccoon	Connecticut	0.67	1.00	0.95	0.03
	Maine	0.19	1.00	0.86	0.08
	Massachusetts	0.49	1.00	0.93	0.06
	New Hampshire	0.12	1.00	0.86	0.10
	Rhode Island	0.81	1.00	0.96	0.03
	Vermont	0.33	0.99	0.85	0.10
	New England	0.12	1.00	0.87	0.09
Red fox	Connecticut	0.08	0.97	0.68	0.12
	Maine	0.11	0.98	0.63	0.08
	Massachusetts	0.07	0.97	0.63	0.13
	New Hampshire	0.07	0.95	0.62	0.08
	Rhode Island	0.08	0.95	0.62	0.17
	Vermont	0.10	0.98	0.67	0.11
	New England	0.07	0.98	0.64	0.10
Striped skunk	Connecticut	0.20	0.99	0.87	0.08
	Maine	0.00	0.99	0.76	0.20
	Massachusetts	0.03	1.00	0.82	0.16
	New Hampshire	0.00	0.99	0.66	0.27

	Rhode Island	0.71	0.99	0.90	0.03
	Vermont	0.01	0.99	0.64	0.26
	New England	0.00	1.00	0.75	0.22
White-tailed deer	Connecticut	0.00	1.00	0.83	0.23
	Maine	0.00	1.00	0.93	0.07
	Massachusetts	0.00	1.00	0.79	0.26
	New Hampshire	0.00	1.00	0.90	0.11
	Rhode Island	0.00	0.99	0.70	0.32
	Vermont	0.00	1.00	0.91	0.08
	New England	0.00	1.00	0.89	0.15
Wild turkey	Connecticut	0.19	1.00	0.79	0.19
	Maine	0.13	1.00	0.61	0.14
	Massachusetts	0.19	1.00	0.73	0.19
	New Hampshire	0.13	0.99	0.70	0.13
	Rhode Island	0.22	1.00	0.74	0.19
	Vermont	0.04	1.00	0.77	0.17
	New England	0.04	1.00	0.68	0.17

Table 2.7. State-based species richness information for 10 wildlife species in the New England region of the northeastern United States. Species richness was calculated using aggregate occurrence estimates from species-specific distribution models for 10 wildlife species. Species models were fit using expert-opinion data and generalized linear mixed modeling.

Region	Minimum	Maximum	Mean	Standard deviation
Connecticut	2.50	8.35	6.68	1.24
Maine	2.52	8.58	7.32	0.64
Massachusetts	2.59	8.72	6.61	1.41
New Hampshire	2.42	8.41	7.19	0.81
Rhode Island	2.51	8.30	6.13	1.55
Vermont	2.69	8.68	7.47	0.73
New England	2.42	8.72	7.16	0.94

2.9. Figures

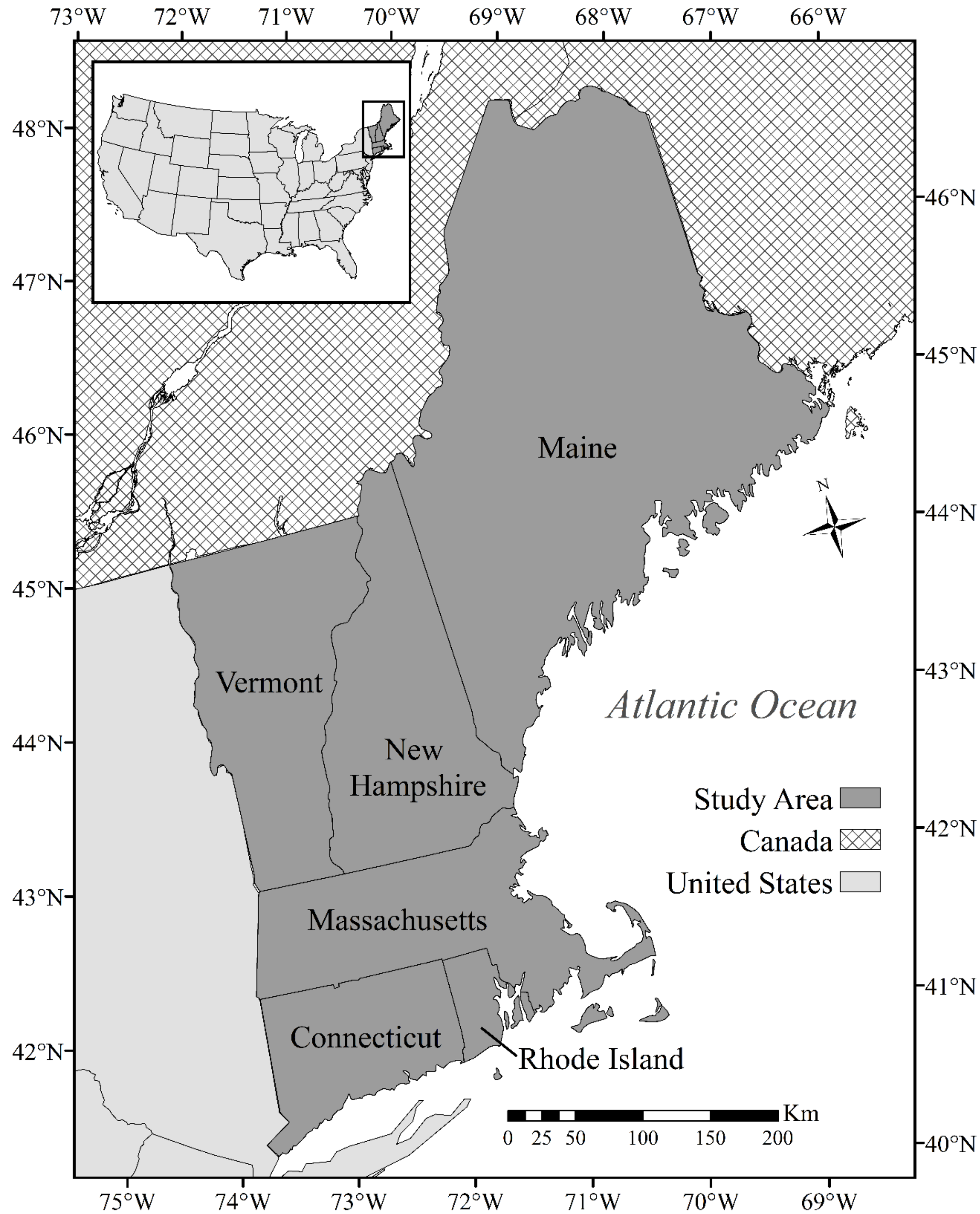

Figure 2.1. The study area (dark gray) within the northeastern United States (light gray). The study area included the full extent of the six New England states (Rhode Island, Connecticut, Massachusetts, Vermont, New Hampshire, and Maine).

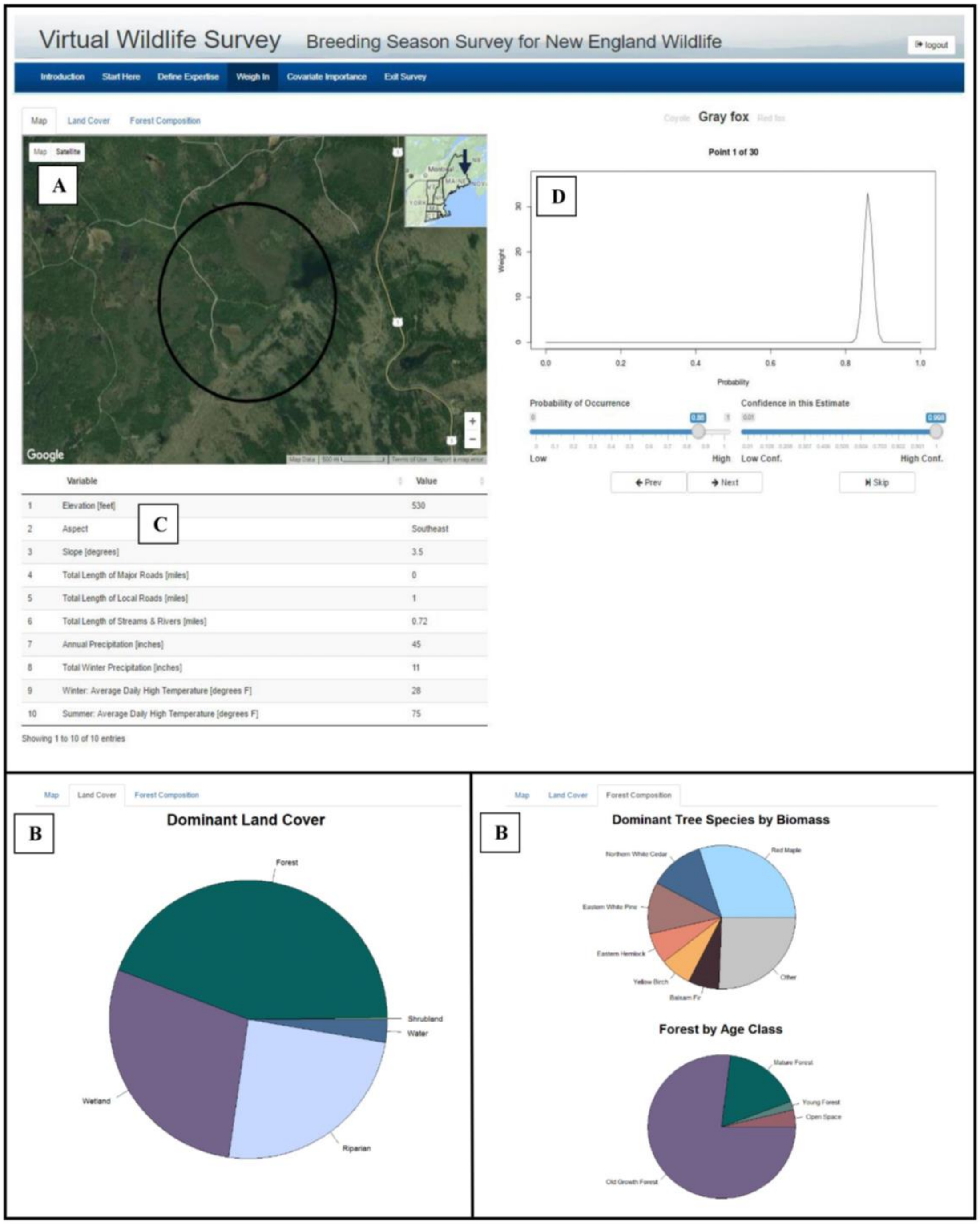

Figure 2.2. Expert elicitation survey interface: A) interactive satellite map; B) additional images tabs (found to the right of the Map tab, above the satellite image) displaying Land Cover and Forest Composition pie charts; C) table of covariates and corresponding site values; and D) expert response sliders and linked output graph.

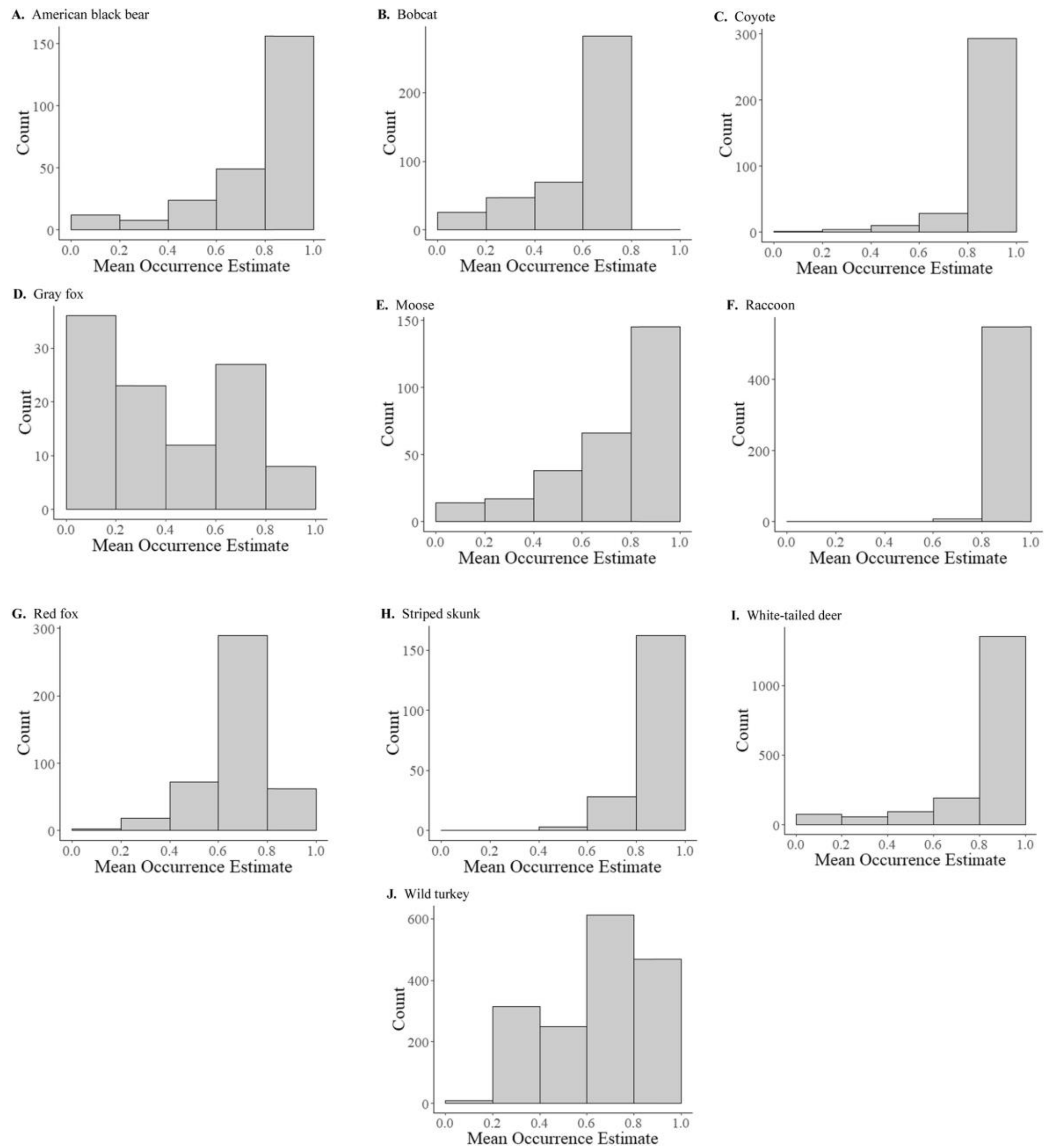

Figure 2.3. Distribution of model estimated mean occurrence at sites with positive occurrence records (i.e., presence data). Species presence data were sourced from iNaturalist and included community-sourced occurrence records for all focal species throughout the New England region of the northeastern United States. Presence locations were buffered (circular; 100m radius) and model estimated mean occurrence was calculated for each site. Histograms show the distribution of mean occurrence estimates. Note that the y-axis scale is different among species. The majority of the species models estimated high occurrence at >70% of the presence locations indicating that that models have strong predictive ability.

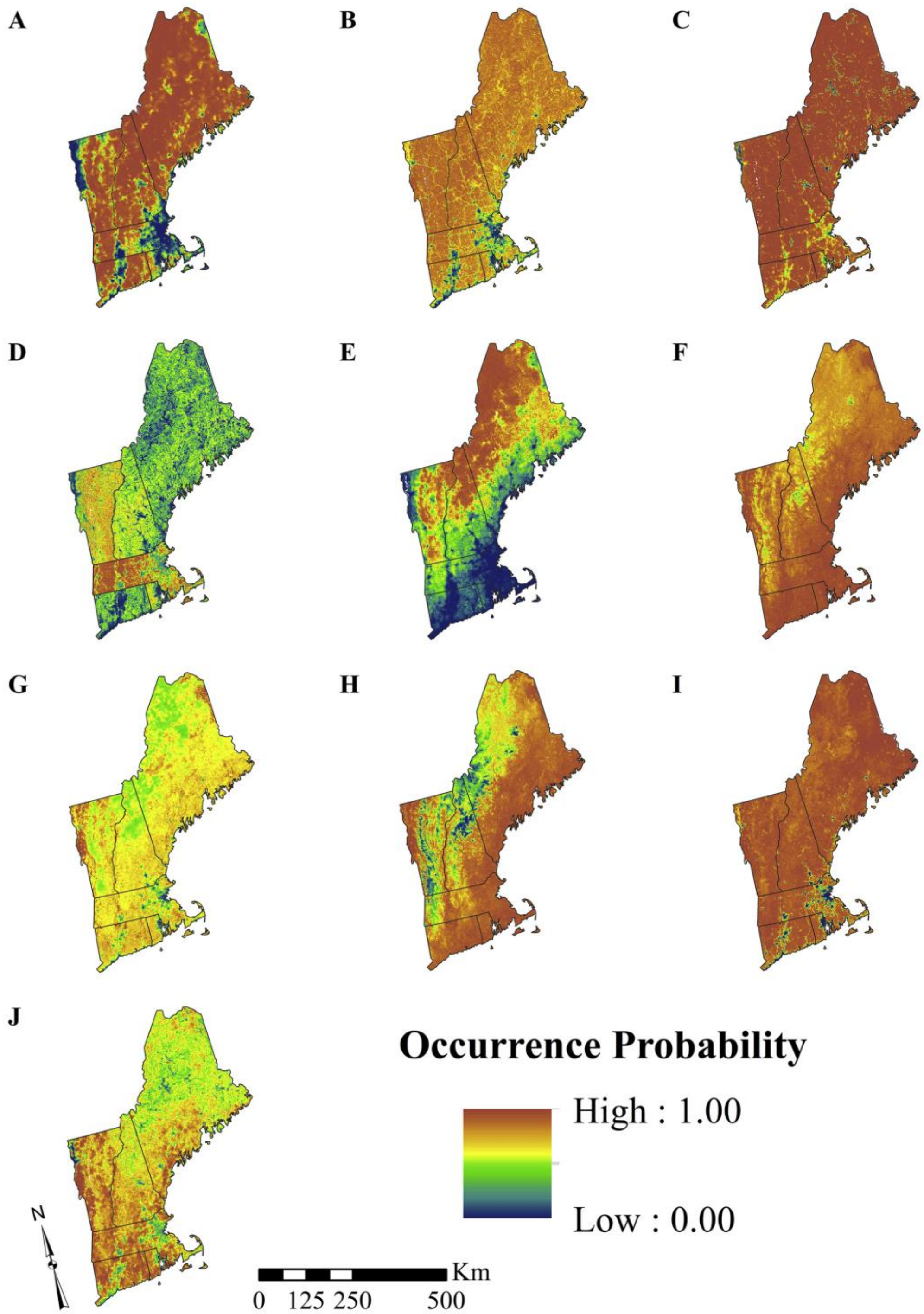

Figure 2.4. Estimated occurrence of 10 focal wildlife species (A – J) in the New England region of the northeastern United States. Occurrence estimates were based on species-specific distribution models fit using expert-opinion data and generalized linear mixed modeling. Species models incorporated site and expert associated random intercept effects and fixed habitat effects. Distribution maps correspond with the following species: A) American black bear, B) Bobcat, C) Coyote, D) Gray fox, E) Moose, F) Raccoon, G) Red fox, H) Striped skunk, I) White-tailed deer, and J) Wild turkey.

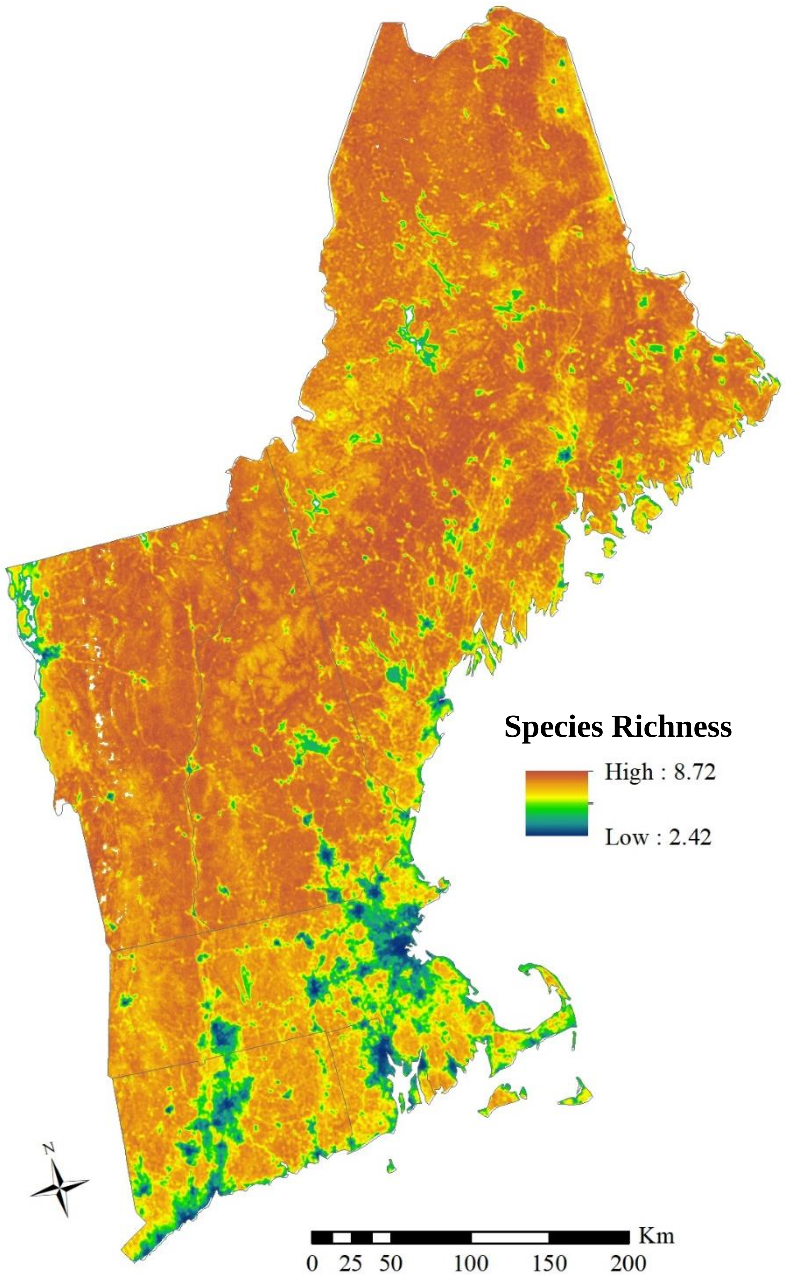

Figure 2.5. Aggregate probability of occurrence for 10 focal wildlife species in the New England region of the northeastern United States. Occurrence estimates were averaged from species-specific distribution models, each fit using expert-opinion data and generalized linear mixed modeling.

CHAPTER 3: DRIVERS AND CONSEQUENCES OF ALTERNATIVE LANDSCAPE FUTURES ON WILDLIFE DISTRIBUTIONS IN NEW ENGLAND, USA

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3.1. Abstract

In an era of rapid climate and land transformation, it is increasingly important to understand how future changes impact natural systems. Scenario studies can offer the structure and perspective needed to understand the impacts of change and help inform management and conservation decisions. We implemented a scenario-based approach to assess how two high impact drivers of landscape change influence the distributions of managed wildlife species (n = 10) in the New England region of the northeastern United States. We used expert derived species distribution models (SDM) and scenarios developed by the New England Landscape Futures Project (NELFP) to estimate how species distributions change under various trajectories (n = 5) of landscape change. The NELFP scenarios were built around two primary drivers – Socio-Economic Connectedness (SEC) and Natural Resource Planning and Innovation (NRPI) – and provide plausible alternatives for how the New England region may change over fifty years (2010 to 2060). Our models generally resulted in species occurrence and richness declines by 2060. The majority of species (7 of 10) experienced declines in regional occurrence for all NELFP scenarios, and one species experienced a projected increase in mean regional occurrence for all scenarios. Our results indicate that the NRPI and SEC drivers strongly influenced projected distribution changes compared to baseline projections. NRPI had a greater impact on distribution change for 5 species (coyote, moose, striped skunk, white-tailed deer, and wild turkey), while SEC had a greater impact on 4 species (American black bear, bobcat, raccoon, and red fox); one species (gray fox) was equally influenced by both NRPI and SEC. These results emphasize the importance of integrating both natural resource planning and socio-economic factors when addressing issues of distribution change and offer insights that can inform proactive management and conservation planning.

Keywords: climate change; land use change; New England; occurrence probability; scenarios; species distribution models (SDMs); species richness; wildlife.

3.2. Introduction

Humans are a dominant driver of landscape change (Díaz et al., 2019; Vitousek et al., 1997). Historical alterations in land use, primarily the conversion of undisturbed forest to other forms of land use like agriculture and urban development, have resulted in the modification of landscapes at a global scale (Díaz et al., 2019; Foley et al., 2005). The rate of landscape modification is accelerating as human-dominated land use continues to expand worldwide (Klein Goldewijk et al. 2011; Seto et al. 2012). More than 30% of the world's land area is already under some degree of development and over 70% of the all forests are in close proximity (< 1 km) to a non-forest edge (Foley et al., 2005; Haddad et al., 2015). With less than 15% of the world's terrestrial land under protection, natural ecosystems are highly susceptible to modification (UNEP-WCMC & IUCN, 2016).

Natural ecosystems are also exposed to the escalating pressures of shifting climatic conditions due to human activities (IPCC, 2014; Walther et al., 2002). With a global temperature increase of ca. 1 °C over the past century and rates of warming nearly doubling over the latter quarter of the century, natural landscapes are subject to climate-induced changes at accelerating rates (K Hayhoe et al., 2018; IPCC, 2014). The last three decades alone experienced global surface temperatures that were warmer than any preceding decade since 1850 and collectively represent the warmest 30-year period in the past 1,500 years (K Hayhoe et al., 2018; IPCC, 2014).

Land use and climatic shifts can have substantial impacts on wildlife globally (Chen, Hill, Ohlemüller, Roy, & Thomas, 2011; Díaz et al., 2019; Root et al., 2003; Thomas et al., 2004). Changes in land use and climate can alter the quality and distribution of habitat (e.g., shifting the composition, structure, and configuration of plant communities), availability of food, prevalence of parasites and diseases, and frequency and intensity of physiological stress from heat or drought (Díaz et al., 2019; Rustad et al., 2012). While these changes can have considerable consequences for wildlife, information gaps and uncertainty around climate and land use trajectories currently limit our understanding of how future changes may impact wildlife species.

In the New England region of the northeastern United States (US), which covers six states and nearly 200,000 km^2, the recent and historic effects of climatic change and land use are evident for some species. For example, Canada lynx (*Lynx canadensis*) has experienced a distribution shift toward higher latitude and elevation in response to landscape change and warming conditions (Koen, Bowman, Murray, & Wilson, 2014; Laliberte & Ripple, 2004). Similarly, warming climate conditions have benefited parasites like winter tick (*Dermacentor albipictus*) that have impacted moose (*Alces alces*) populations by reducing fitness and causing periodic epizootics (> 50% die-offs) in some regions (Jones et al., 2019; Murray et al., 2006). With the continued pressures of human population expansion, urban development and sprawl, and warming climate trends, New England's natural landscapes are expected to experience rapid modification over the next half-century (Dupigny-Giroux et al., 2018; Duveneck & Thompson, 2019; Olofsson et al., 2016; Thompson et al., 2017; White, Morzillo, & Alig, 2009).

Rapidly changing environments present considerable management challenges for federal and state agencies charged with maintaining viable wildlife populations. Across the New England region, wildlife management largely occurs at the state-level, and is characterized by different strategies for species, which creates challenges for broader-scale conservation planning (Aycrigg et al., 2016; McBride et al., 2017). Scenario-based planning offers an approach to better understand the larger-scale impacts of change that can lead to more effective, proactive decision-making for species (Carpenter & Folke, 2006; Thompson et al., 2016). In New England, studies have been initiated to improve understanding and anticipate future trajectories of land-use and natural infrastructure (Duveneck & Thompson, 2019; McBride et al., 2017; McGarigal et al., 2017; Thompson et al., 2017). For example, the Designing Sustainable Landscapes (DSL) project developed a Landscape Change, Assessment and Design (LCAD) model to simulate current trends scenarios for landscape change in the northeastern US and assess the associated ecological impacts (McGarigal et al., 2017).

Another study, the New England Landscape Futures Project (NELFP), simulated not only future landscape conditions under recent trends (Duveneck & Thompson, 2019; Thompson et al., 2017), but also simulated plausible futures developed by stakeholders considering alternative policy decisions. Led by the Harvard Forest Long-Term Ecological Research program and the Scenarios, Services, and Society Research Coordination Network, this study developed four alternative scenarios of how New England's landscape may look over a fifty-year time period (2010 to 2060). These scenarios represent plausible alternatives to recent trends that are built around two uncertain, yet highly influential drivers of landscape change: Natural Resource Planning & Innovation (NRPI) and Socio-Economic Connectedness (SEC; McBride et al., 2017; Thompson et al., 2019). The NRPI axis provides the extent to which the government and private sector invest in proactive land-use planning, ecosystem services, and technological advances for resource use, primarily land, energy, and water. The SEC axis provides the extent of local or global connectivity in population migration, culture, economic markets, trade policy, goods and services, and climate policy. These primary drivers are used as the basis for the four alternative scenarios to the continuation of a recent trends scenario (i.e., “Business-As-Usual”): “Connected Communities”, “Yankee Cosmopolitan”, “Go It Alone”, and “Growing Global”. The NELFP scenarios were collaboratively designed by stakeholders, simulation modelers, and researchers throughout New England and provide plausible trajectories of landscape change that incorporate informed simulations of climate, development, agriculture as well as forest structure and composition. However, wildlife species have not been assessed in the context of these scenarios.

Given the recent rates of landscape change in the New England region, combined with extensive evidence that changing climate, human expansion, and land transformation can have negative consequences for many wildlife species, decision-makers are faced with two crucial and unresolved questions: 1) How will changing climate and landscape conditions impact the future viability and distribution of wildlife species in the region? 2) How do social drivers, such as NRPI or SEC, influence species distribution change in a future New England landscape? With uncertainty around natural resource planning, innovation and socio-economic factors, we need a systematic approach that addresses these questions and advances our understanding of the complex, dynamic systems that affect wildlife. Approaching these questions proactively may 1) lead to more efficient, cost effective and sustainable conservation and management practices, 2) improve the state of biodiversity and natural systems, and 3) help protect iconic species and the benefits they offer to humans and society (Güneralp et al., 2013).

By considering forecasted shifts in species distributions, wildlife agencies can plan for long-term conservation at multiple spatial and temporal scales.

We addressed these questions by evaluating how climate change and different trajectories of land-use may influence a group of commonly managed wildlife species in the New England region. We used expert-derived species distribution models (SDMs) developed by Pearman-Gillman et al. (2020) and the NELFP scenarios to: 1) estimate and map the future distributions of 10 focal species under five alternative scenarios, and assess regional species richness patterns, 2) quantify changes in species distributions under each scenario, and 3) compare distribution change across scenarios to quantify the impacts of SEC and NRPI, and identify the drivers with the greatest potential influence on individual and multi-species change.

3.3. Methods

Study Area. The study area encompassed the six New England states (Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and Maine) in the northeastern US (Fig. 3.1). The region spans 186,458 km^2 with topography ranging from coastal plains to mountain peaks reaching nearly 2,000 m above sea level. Climatic conditions vary by season and geographic location throughout the region. Long-term climate records indicate an average annual precipitation of 104 cm (range: 79 cm to 255 cm) and a mean regional temperature ranging from 6 °C (Jan) to 19 °C (Jul) (Huntington et al., 2009).

The New England region supports a growing human population (14,853,290 in the 2018 U.S. Census) with three-quarters of the population concentrated in the major metropolitan areas of southern portion of this region (U.S. Census Bureau, 2019). The uneven distribution of people contributes to regional variability in land use patterns and intensities with large population centers in the south and more rural undeveloped landscapes in the north. Currently, approximately 80% of the region is covered by forest (Foster et al., 2010). Forested regions are ecologically diverse with areas dominated by northern hardwood, spruce-fir, oak-hickory, and pitch pine forest types (Brooks et al., 1992; Duveneck et al. 2015). Non-forest areas of New England are primarily composed of development (9.3%), agriculture (5.9%) and water (12.3%; Homer et al. 2015).

Focal Species. We focused our analysis on harvested wildlife species (n = 10) that occur widely throughout the region. This group includes 9 mammals: American black bear (*Ursus americanus*), Bobcat (*Lynx rufus*), Coyote (*Canis latrans*), Gray fox (*Urocyon cinereoargenteus*), Moose (*Alces alces*), Raccoon (*Procyon lotor*), Red fox (*Vulpes vulpes*), Striped skunk (*Mephitis mephitis*), and White-tailed deer (*Odocoileus virginianus*); and 1 bird species: Wild turkey (*Meleagris gallopavo*). We selected these species because they are largely the emphasis of wildlife management at the state-level. Game species are important economically and culturally as they are harvested and often sought by wildlife watchers. Several of these species also exert large ecological effects on ecosystems, such as moose and deer (Horsley, Stout, & DeCalesta, 2003; C. G. Jones, Lawton, & Shachak, 1994; Pastor et al., 1998).

Objective 1 – Map species future distributions

Distribution Models. We used species distribution models (SDMs) developed by Pearman-Gillman et al. (2020) to estimate and map distributions of the abovementioned focal species. Models were developed using expert elicitation techniques. Briefly, we elicited expert opinion data on the probability of occurrence of each focal species from wildlife and conservation professionals throughout the study region using the online survey tool, AMSurvey (https://code.usgs.gov/vtcfwru/amsurvey). We then used mixed-model methods and stepwise model selection techniques (Bates et al., 2014; Burnham & Anderson, 2002; Zar, 1999) to develop a model for each species that predicted probability of occurrence as a function of landscape and climate variables (Table 3.1). Models included variables that were identified in the literature, selected by experts, or were highly correlated with perceived occurrence (Tables 3.2 & 3.3). Validation tests indicated that the models performed well for predicting species occurrence across the New England region (Pearman-Gillman, Katz, et al., 2020).

Scenario Simulations. To estimate species distributions under projected conditions, we applied each SDM to the recent trend and four NELFP scenarios (McBride et al., 2017; Thompson et al., 2019), each defined by their degree of Natural Resource Planning & Innovation (NRPI) and Socio-Economic Connectedness (SEC). For details about the NELFP scenario development process, detailed scenario descriptions, and scenario figures, see McBride et al. (2017) and Thompson et al. (2019). A summary of each scenario is described below:

1. ***Business-As-Usual (Recent Trends).*** This scenario represents a baseline projection extended from the region's contemporary circumstances. It depicts the linear continuation of New England's recent trends in the rate and spatial patterns of landscape change. This scenario offers a baseline for evaluating the other scenarios of change.
2. ***Connected Communities (High NRPI & Local SEC).*** In this scenario, the New England population has slowly increased over the past fifty years and

communities are coping with climate change by anchoring in place, making local culture and the protection of local resources important government and community priorities. Concerns about global unrest and the environmental impacts of global trade led New England communities toward a more community-focused lifestyle. Strengthened local relations and advances in local green energy contribute to more self-reliant communities. Heightened community interest and public policies protected wildlands, strengthened local economies and fueled growing local markets (primarily local food, wood, and recreation).

3. ***Yankee Cosmopolitan (High NRPI & Global SEC).*** This scenario describes a future in which New England remains relatively resilient to climate change, has become a leader in research and technology, and subsequently experienced substantial population growth. The region's population has largely grown due to an influx of international migrants seeking areas less vulnerable to the effects of climate change (e.g., heat, drought, sea-level rise). As a world leader in biotech and engineering, New England has a large demand for a skilled labor work force and established itself as a major center of economic and population growth within the U.S. Most development has occurred in urban areas with sprawl occurring as populations grow faster than the infrastructure can support. In a globally connected world, the region relies on imports for most food products. With a global shift towards sustainability, New England has invested in land protection, ecosystem services, and its carbon storing forests.

4. ***Growing Global (Low NRPI & Global SEC).*** In this scenario, New England has remained relatively sheltered from the effects of climate change and has become a desirable location for migrants seeking more environmentally stable areas. This has led to population and development increases that have outpaced local planning efforts and contributed to city sprawl, haphazard expansion of development, poor transportation infrastructure and inefficient energy use. Underprepared government entities have struggled to support the region's growing population leading to higher levels of privatized municipal services, limited natural resource planning and sharp declines in land protection. With trade barriers lifted, global trade has amplified and the U.S. has experienced a surge in the production and export of commodity crops. Increased agriculture, development and growing biofuel markets have increased the degradation and conversion of New England's forested land. Globalization and increased transportation demands have strengthened a global reliance on conventional and cheap energy sources (fossil fuels). With little innovation and no global commitment to climate action, the world remains divided on issues of climate change and renewable energy.
5. ***Go It Alone (Low NRPI & Local SEC).*** This scenario describes a New England with fairly low economic opportunity, population growth, and land development. A lack of global economic connectivity, tightened national borders, and reductions in national budgets have limited the nation's ability to deal with unemployment, demographic change, and climate resilience. Global efforts at climate adaptation have failed and conventional energy sources still

> dominate. In New England, the lack of regulation decreased natural resources protection, technological innovation and availability of goods and municipal services. With reduced access to global energy markets, failure to launch new energy development projects and the degradation of conventional energy infrastructure, the price of energy has continued to rise. Increased energy and export expenses have reduced timber harvesting and commercial agriculture contributing to economic collapse. New residential developments lack appropriate planning and most public authorities lack the funds to maintain critical infrastructure such as roads and sewers. High energy costs, poor infrastructure planning and failure to fund climate change adaption has left communities isolated and heavily reliant on local resources. Poor planning and extractive use have significantly degraded the region's ecosystem services and considerably decreased quality of life.

Each scenario narrative was translated into spatial patterns of change using methods described by Thompson et al. (2019, 2017) and Duveneck and Thompson (2019). Briefly, these simulations were developed in two stages: first using a spatially explicit cellular land change model, Dinamica Environment for Geoprocessing Objects (Dinamica EGO 2.4.1; Soares-Filho et al. 2009) and the second using a forest landscape succession model, LANDIS-II v6.2 (Scheller et al., 2007). Dinamica was used to simulate fifty years (2010 – 2060) of forest loss, land-use change, and land protection relative to the underlying narrative of each NELFP scenario. This process produced scenario specific land cover spatial layers (30 x 30 m) for forest, agriculture, high density development, and low density development (Thompson et al., 2019, 2017). Using these land cover spatial layers, a LANDIS-II forest simulation was run on all forest pixels for each scenario from 2010 to 2060 to simulate the growth, dispersal, and mortality of 32 individual tree species (Duveneck & Thompson, 2019). Climate change was incorporated into each scenario using climate projections (i.e., monthly maximum temperature, minimum temperature, and precipitation) based on the assumptions of the Representative Concentration Pathway (RCP) 8.5 emission scenario (IPCC, 2013) as simulated by to the Hadley Global Environment Model v.2-Earth System (HADGE) Global Circulation Model (GCM). This climate future includes an increase in temperature and slight increase in precipitation in New England by 2060. Much larger changes in climate are expected beyond 2060 (IPCC, 2014). Indeed, the effects of climate in these simulations were largely outweighed by the effects of land use (Duveneck & Thompson, 2019). The LANDIS-II simulations included changes in forest composition relative to a warming climate, development, and harvest patterns for the recent trends scenario (Duveneck & Thompson, 2019) and each alternative NELFP scenario. The resulting above-ground biomass layers by tree species were used for modeling wildlife distributions (see below). Additional spatial layers utilized came from the HADGE GCM simulated climate data, Dinamica land cover outputs, and recent conditions land cover data (see Table 3.2).

Mapping Projected Species Distributions. We applied the SDMs to the simulated spatial layers generated for each NELFP scenario (Table 3.2) to map the future distributions of each species in New England. Species distribution maps were generated for each scenario by 1) multiplying the scenario's covariate rasters by the corresponding SDM coefficients for a given species, then 2) summing the resulting raster layers to obtain logit scores for every pixel, and 3) transforming the logits to create a raster of occurrence probabilities. This process generated species-specific distribution maps for each scenario (n = 5). We also created species richness maps by stacking the 10 individual species rasters and summing the values in each pixel to generate an index of species richness for each future scenario (Sauer et al., 2013). Richness values could potentially vary from 0 (no species present) to 10 (all species present). We developed distribution maps and species richness maps using the raster package (Hijmans, 2016) in the statistical computing software, R (R Core Team, Vienna, Austria, 2019).

Objective 2 – Quantify scenario-specific distribution change

Scenario-specific distribution maps were compared against current distribution maps to estimate shifts (i.e., recession or expansion) in regional distributions. We compared each species' current distribution (Pearman-Gillman, Katz, et al., 2020) to each scenario's projected distribution. Current distribution map pixels were subtracted from superimposed projected distribution map pixels to calculate values of projected change. Pixels with negative distribution change values represented locations of declining species occurrence and pixels with positive values represented locations of increasing occurrence.

Objective 3 – Compare the impacts of NRPI and SEC on wildlife species

***Isolating Driver Impacts*.** Each NELFP scenario was built around two directional drivers of land use change – either high or low NRPI, and global or local SEC. For each species, we combined (averaged) distribution change information across scenarios with a common directional driver, marginalizing the influence of the second driver. For example, to obtain a distribution shift under the high NRPI driver, we averaged the two high NRPI scenarios (Yankee Cosmopolitan and Connected Communities), marginalizing over the directional SEC drivers. As a second example, to obtain a distribution shift for each species under the local SEC driver, we averaged the two local SEC scenarios (Go It Alone and Connected Communities), marginalizing over the directional NRPI drivers. We used this process to provide comparative baselines for NELFP's two primary drivers of land use change. Next, we subtracted the Recent Trends (RT) values from the isolated driver maps to account for forecasted baseline changes over the 50-year time-step, effectively removing the external factors of change that were not a product of shifts produced by the NRPI or SEC drivers. The resulting maps depict the potential influence of each driver on species occurrence in order to help isolate areas that will benefit from high or low investment in innovation and natural resources, or areas that are most vulnerable to globalized or localized growth.

Quantify & Compare Drivers. We calculated descriptive statistics (minimum, maximum, mean, standard deviation, and quartiles) across each isolated driver landscape to quantify the effect each driver had on species occurrence. This provided comparable statistics and allowed us to assess how and to what degree the NRPI and SEC drivers are expected to impact wildlife in the future. As a final comparison, we calculated the absolute difference that NRPI and SEC had on species occurrence (i.e., the difference between high and low NRPI and global and local SEC). This allowed for quantitative comparisons between the two primary drivers of change and indicated which driver may have a greater impact on wildlife species.

3.4. Results

Objective 1 & 2 – Future distributions and projected distribution change

The projected distribution maps varied among species and the 5 scenarios. For all species but one (red fox), average regional occurrence likelihoods were projected to decline under nearly all scenarios by 2060 (see Appendix C.1 for individual species maps). The locations and overall extent of distribution decline varied among species and scenarios. Generally, focal species distributions shifted away from areas of potential development expansion (largely in the southern New England states), and remained relatively stable in the northern and central regions of New England where less development was projected and timber harvest, forest management, and agriculture were largely driving landscape change (Appendix C.1).

Projected declines in species occurrence probabilities were accompanied by declines in focal species richness. A regional average focal species richness (μ_s) of 7.16 was estimated for the New England landscape in 2010 representing current conditions (Fig. 3.2a). All future scenarios at 2060 projected lower focal species richness than was estimated for current conditions (Fig. 3.2b-f). Of the future scenarios, average regional focal species richness was lowest under the Yankee Cosmopolitan (YC; μ_s = 6.44, a 10.1% decline) and Business-As-Usual (RT; μ_s = 6.54, an 8.7% decline) scenarios (Fig. 3.2). The Growing Global (GG) scenario had the highest average regional focal species richness (μ_s = 6.84, a 4.4% decline), followed by Go It Alone (GA; μ_s = 6.72, a 6.2% decline) and Connected Communities (CC; μ_s = 6.64, a 7.2% decline; Fig. 3.2).

For individual species, the greatest distribution declines across scenarios were projected for American black bear, gray fox, moose, and wild turkey (Fig. 3.3). Considerably lower levels of decline were observed for bobcat, raccoon, and striped skunk, and minimal declines in mean regional occurrence were projected for coyote and white-tailed deer (Fig. 3.3). An increase in regional occurrence was projected for red fox across all scenarios (Fig. 3.3g).

Objective 3 – Impacts of NRPI and SEC on wildlife species

SEC had a greater impact on distribution change than NRPI for four species, including American black bear, bobcat, raccoon and red fox (Table 3.4). ***American black bear*** distribution declined under the recent trends (RT, i.e., Business-As-Usual) scenario and all 4 driver isolated simulations (Fig. 3.4a). Both High NRPI and Low NRPI drivers led to distribution loss similar to the 2060 RT projection. Local SEC was the only driver that simulated higher regional occurrence than the RT baseline (Fig. 3.4b). Of the 4 drivers, Local SEC simulated the highest regional occurrence for American black bear, while Global SEC simulated the lowest regional occurrence (Table 3.3, Fig. 3.4b, see Appendix C.2 for species-specific maps of driver isolated distribution change). ***Bobcat*** distribution declined under RT and the 4 driver isolated simulations (Fig. 3.4a). Both High NRPI and Low NRPI drivers led to distribution loss similar to the 2060 RT projection. Global SEC was the only driver that projected lower regional occurrence than the RT baseline (Fig. 3.4b). Of the 4 drivers, Local SEC simulated the highest regional occurrence for bobcat, while Global SEC simulated the lowest regional occurrence (Table 3.3, Fig. 3.4b, Appendix C.2). ***Raccoon*** distribution declined under RT and the 4 driver isolated simulations (Fig. 3.4a). Both High NRPI and Local SEC drivers projected slightly lower regional occurrence than the 2060 RT projection; Low NRPI and Global SEC projected higher regional occurrence than RT (Fig. 3.4b). Of the 4 drivers, Global SEC simulated the highest regional occurrence for raccoon, while Local SEC simulated the lowest regional occurrence (Table 3.3, Fig. 3.4b, Appendix C.2). ***Red fox*** distribution increased under RT and the 4 driver isolated simulations (Fig. 3.4a). All 4 drivers led to distribution gain similar to the 2060 RT projection. Local SEC was the only driver that projected lower regional occurrence than the RT baseline (Fig. 3.4b). Of the 4 drivers, Global SEC simulated the highest regional occurrence for red fox, while Local SEC simulated the lowest regional occurrence (Table 3.3, Fig. 3.4b, Appendix C.2).

NRPI had a greater impact on distribution change than SEC for five species, including coyote, moose, striped skunk, white-tailed deer, and wild turkey (Table 3.4). ***Coyote*** distribution declined under RT and all driver isolated simulations (Fig. 3.4a). All 4 drivers projected higher regional occurrence than the 2060 RT projection (Fig. 3.4b). Of the drivers, Low NRPI simulated the highest regional occurrence for coyote (Table 3.3, Fig. 3.4b, Appendix C.2). ***Moose*** distribution declined under RT and the 4 driver isolated simulations (Fig. 3.4a). High NRPI was the only driver that projected lower regional occurrence than the 2060 RT projection (Fig. 3.4b). Of the 4 drivers, Low NRPI simulated the highest regional occurrence for moose, while High NRPI simulated the lowest regional occurrence (Table 3.3, Fig. 3.4b, Appendix C.2). The Local SEC driver also had a substantial impact on distribution change, leading to considerably higher mean regional occurrence than expected under RT. ***Striped skunk*** distribution declined under RT and all driver isolated simulations (Fig. 3.4a). All 4 drivers projected higher regional occurrence than the 2060 RT projection. Of the 4 drivers, Low NRPI simulated the highest regional occurrence for striped skunk (Table 3.3, Fig. 3.4b, Appendix C.2). The Global SEC driver had a similar impact as Low NRPI, leading to higher mean regional occurrence than expected under RT. ***White-tailed deer*** distribution increased under RT and declined under all driver isolated simulations (Fig. 3.4a). All 4 drivers minimize regional occurrence for white-tailed deer (Fig. 3.4b). Of the 4 drivers, Low NRPI had the largest impact on distribution change and simulated the lowest regional occurrence for white-tailed deer (Table 3.3, Fig. 3.4b, Appendix C.2). ***Wild turkey*** distribution declined under RT and all driver isolated simulations (Fig. 3.4a). All 4 drivers projected higher regional occurrence than the 2060 RT projection; with Low NRPI and Global SEC projecting higher regional occurrence than High NRPI and Local SEC (Fig. 3.4b). Of the drivers, Low NRPI simulated the highest regional occurrence for wild turkey (Table 3.3, Fig. 3.4b, Appendix C.2).

For one species, gray fox, SEC and NRPI had an equal influence on distribution change (Table 3.4). ***Gray fox*** distribution declined under RT and all driver isolated simulations (Fig. 3.4a). All 4 drivers projected higher regional occurrence than the 2060 RT projection; with Low NRPI and Global SEC projecting considerably higher regional occurrence than High NRPI and Local SEC (Fig. 3.4b). Of the drivers, Low NRPI simulated the highest regional occurrence for gray fox (Table 3.3, Fig. 3.4b, Appendix C.2).

Generally, Low NRPI and Global SEC were the most influential directional drivers of distribution changes (Fig. 3.5). Low NRPI had the largest impact on regional distribution change for 6 of the 10 species (coyote, gray fox, moose, striped skunk, white-tailed deer, and wild turkey), while Global SEC had the largest impact for two species (raccoon and red fox) and had a relatively large influence on distribution change for the remainder of the focal group. Of the four drivers, High NRPI had the smallest impact on distribution change for nearly all species, and Local SEC had a large impact for a few species but was otherwise less influential than the Low NRPI and Global SEC drivers

(Fig. 3.5). When comparing the difference between high vs. low NRPI and local vs. global SEC, we found a nearly 50/50 split in the focal group for which the primary driver had a greater impact on distribution change (Table 3.4).

3.5. Discussion

The New England region is a large landscape that covers six US states and includes some of the largest expanses of hardwood forest and metropolitan areas in the country. Climate change and the pace of urban development has increased substantially in recent years, and the impacts of these changes on wildlife are largely unknown (K Hayhoe et al., 2018; Seto et al., 2012). Our analysis suggests that a continuation of current trends will result in declines in the distribution of harvested species, which are important ecologically, socially, and economically in the region (U.S. Department of the Interior, U.S. Fish and Wildlife Service, U.S. Department of Commerce, & U.S. Census Bureau, 2016). For example, in Vermont, hunting, trapping, and shooting are important activities to residents, major contributors to the state's economy, and are largely focused on species that exert strong ecological impacts on forest ecosystems like moose, deer, and bear (Horsley et al., 2003; Pastor et al., 1998; U.S. Bureau of Economic Analysis, 2019; U.S. Department of the Interior et al., 2016).

Species distributions are predicted to decline for most of the focal species if current climate and land use trends continue. The Business-As-Usual scenario – which simulated climate trends following the RCP 8.5 emission scenario and a continuation recent trends (RT) in land use – resulted in 4.36% less forest cover by 2060 (Duveneck & Thompson, 2019) due to increases in development and agricultural land cover (37% and <5% more, respectively; Thompson et al., 2019), and less favorable conditions for the majority of the wildlife species considered. Under this scenario, eight of the ten focal species demonstrated a decrease in regional occurrence. Only the red fox and white-tailed deer experienced an increase in regional occurrence (29.6% and 0.5%, respectively). The red fox is the widest ranging member of the Carnivora and capable of living in a variety of environments, including deserts, forests, tundra, and urban environments largely due to its physiology and behavioral plasticity (Lariviere & Pasitschniak-Arts, 1996; Tesky, 1995; Voigt, 1987). Similarly, white-tailed deer often occur at the interface between natural and developed areas and occupy a variety of habitat types (Swihart, Picone, DeNicola, & Cornicelli, 1993). Increases in these species distributions probably reflects their ability to adapt to the current trends of environmental change.

Among the species expected to decline if recent trends continue, four showed low to moderate declines in regional occurrence, including bobcat, coyote, raccoon, and striped skunk (ranging between a 3.0% and 6.6% decline by 2060). By comparison, American black bear, gray fox, moose, and wild turkey experienced relatively large reductions in distribution and average regional occurrence (ranging between 15.7% and 51.7% decline). These species are generally more sensitive to development and climate shifts, which may explain the projected negative impacts on distribution (COSEWIC, 2015; Environment and Climate Change Canada, 2018; Evans, 2016; H. E. Johnson et al., 2018; Lavoie, Blanchette, Larivière, & Tremblay, 2017; Renecker & Hudson, 1986; Roberts & Porter, 1998; Rustad et al., 2012). High levels of decline are concerning, especially for moose and gray fox, which have been identified as Species of Greatest Conservation Need by one or more of the New England states (Maine Dept. of Inland Fisheries and Wildlife, 2015; Massachusetts Division of Fisheries and Wildlife, 2015;

New Hampshire Fish and Game Department, 2015; Rhode Island Department of Environmental Management Division on Fish and Wildlife, 2015; Vermont Fish & Wildlife Department, 2015). Additional assessments have indicated recent population and distribution declines for moose in New England (Timmermann & Rodgers, 2017; Wattles & DeStefano, 2011) and many other regions in North America (Broders, Coombs, & Mccarron, 2012; Lenarz, Fieberg, Schrage, & Edwards, 2010; D. L. Murray et al., 2006).

The Business-As-Usual scenario presents one plausible future, but we also explored the effects of other alternative futures on wildlife. The NELFP scenarios provided a set of alternative futures, influenced by climate change, yet based mainly on two social drivers of land use change – natural resource planning and innovation (NRPI) and socio-economic connectedness (SEC). These scenarios accounted for future climate impacts and allowed us to assess how patterns of wildlife occurrence and species richness were influenced by different drivers and trajectories of land use change. Of the four alternative scenarios, Growing Global (GG), Go It Alone (GA), and Connected Communities (CC) all led to higher species richness then RT; Yankee Cosmopolitan (YC) led to lower richness. Similarly, our assessment of the social drivers of change indicated that a low investment in NRPI and a global approach to SEC were most influential on distribution change and species richness.

In terms of land cover change, a low investment in NRPI led to increased rates of timber harvest in the NELFP scenarios. The GA and GG scenarios were built around the low NRPI driver and simulated the highest timber harvest rates of all the scenarios (i.e., 135% and 110% increase in harvest rate compared to RT, respectively) and the highest species richness of all the scenarios. Timber harvest can benefit some species, including some in the focal group (Hunter & Schmiegelow, 2011; Monthey, 1984) by generating important habitats (e.g., early succession forest) and increasing heterogeneity in forest structure and composition (Hansen, Spies, Swanson, & Ohmann, 1991; Hunter & Schmiegelow, 2011). Moose, gray fox, and wild turkey are all species that appear to benefit from increased forest heterogeneity driven by low NRPI. For example, moose distribution was greatest under the GA and GG scenarios; probably because these scenarios resulted in high levels of timber harvest and larger amounts of young forest, which benefit moose (Innes, 2010; Monthey, 1984; Wattles & DeStefano, 2011). However, it is important to recognize that continuation of low NRPI actions and disregard for innovation or more extensive natural resource planning activities will probably have less favorable long-term consequences for many other wildlife species. Climate impacts on forest composition may also have greater long-term consequences for wildlife. For this analysis we simulated climate and land use change 50 years into the future, however, the effects of climate change on forest composition are projected to increase dramatically beyond 50 years (Duveneck & Thompson, 2017; Janowiak et al., 2018). With larger shifts occurring in the second half of the 21st century, wildlife species may experience less favorable conditions over time.

Economic development activities like urban expansion and the conversion of forest to agriculture can also have considerable impacts on species richness by reducing the availability and quality of habitat in the region (Murphy & Romanuk, 2014; Newbold et al., 2015). In the NELFP simulations, the CC and GA scenarios were built around the local SEC driver and led to lower rates of development (i.e., 75% and 25% decrease in development rate, respectively) and higher species richness than the recent trends projection. By comparison, the GG and YC scenarios were built around the global SEC driver and simulated high rates of development (i.e., 180% and 40% increase in development rate compared to recent trends, respectively). These two scenarios resulted in the highest (GG) and lowest (YC) species richness, showing that increased development rates can negatively influence species occurrence, but may not directly translate to lower richness. Rather, other factors including the pattern and intensity of development may be more influential than rate alone. Both global and local SEC drivers altered development patterns and subsequently influenced distribution change – drawing attention to the considerable influence that social and economic factors can have on natural systems, and emphasizing the importance of including these factors in regional planning efforts.

The scenario assessments provide measures of the response of multiple wildlife species to future natural, social, and economic changes in New England. The results provide species information that can aid in landscape decision-making around management and conservation problems (G. D. Peterson et al., 2003). For a given problem, decision-makers can set objectives, then use the models to assess the consequences associated with each scenario, evaluate trade-offs among scenarios, and identify the trajectory that most successfully meets their objectives. As a simple example, a group interested in maximizing black bear in New England could compare occurrence probabilities across the scenarios to evaluate the trade-offs of each type of future scenario; in this case, choosing the GA scenario would be best as it projects the highest regional occurrence for black bear. Information about the GA scenario could then be used to help guide policy and management actions.

The scenarios could also be used in more complex decision-making problems that account for trade-offs across multiple objectives and multiple spatial and temporal scales. For example, the state of Vermont has set a goal of meeting 90% of the state's energy needs through renewables (e.g., solar, wind, forest-derived bioenergy) by the year 2050 (Vermont Department of Public Service, 2016). Considering this objective, Vermont could change following a trajectory similar to the CC scenario – in which advances in local green energy support a more self-reliant community – or the GA scenario – in which poor planning and extractive use significantly degrades the region’s ecosystem services. However, the state also has objectives related to the sustainability of harvested species, other natural resources, and climate change. Decision-making frameworks following principles of Structured Decision Making (Gregory et al., 2012) could be used to evaluate possible impacts of climate change and the trade-offs of each future scenario on renewable energy production, and sustainability of harvested species and other natural resources, which can inform policy actions.

Our assessments of landscape change on wildlife species accounted for several social, ecological, and economic factors based on information from models, expert opinion, and consensus from a consortium of scientists, managers, and community members (i.e., the Scenarios, Services, and Society Research Coordination Network that developed the NELFP scenarios). However, any future scenario projections involve uncertainties. Uncertainty in the SDM parameters has been estimated, which provides a measure of confidence in the occurrence estimates. Other factors not considered in the modeling process, such as species interactions or variable trajectories of climate change, may impact distribution patterns and induce additional uncertainty in the outcome for species (Royle & Dorazio, 2008). For example, coyotes are dominant competitors and have been shown to shape the distribution of other sympatric carnivore species (Fedriani, Fuller, Sauvajot, & York, 2000; W. E. Johnson, Fuller, & Franklin, 1996); changes in their occurrence over time may have impacts on red foxes and gray foxes through competition (Fedriani et al., 2000; W. E. Johnson et al., 1996; Levi & Wilmers, 2012), and even game birds like wild turkey through altered predation risk (Guthrey, 1995). Accounting for the behavioral and ecological complexities of species interactions are challenging, and would require additional (and currently unavailable) data to be integrated into future scenario modeling. Future climate conditions are also largely uncertain and species future distributions may vary considerably under different trajectories of climate change. Here, we simulated future climate conditions based on a single high emissions scenario to aide interpretability and offer distribution projections that account for both climate and land-use change. Considering additional climate scenarios and climate-related factors could provide further insight on species future distribution patterns.

We also used probability of occurrence at a 30 m pixel level as a measure for evaluating the effects of landscape change on a species. Occurrence probability reflects habitat quality, which we assumed also relates to the number of individuals, an important measure for harvest management (e.g., setting harvest quotas or bag limits). A positive relationship between occupancy probability and abundance has been shown for several wildlife species (Blackburn, Cassey, & Gaston, 2006; Zuckerberg, Porter, & Corwin, 2009). However, this relationship is not always consistent and linear (Blackburn et al., 2006). For example, recent trends suggest that gray foxes are expanding in range in the northeastern US and eastern Canada (COSEWIC, 2015; Environment and Climate Change Canada, 2018). However, our projection for gray fox shows a decline in occurrence under the RT scenario. Here, it is important to distinguish range expansion from population growth and increased species occurrence – while the range of gray fox may be expanding, localized shifts in habitat can lead to lower abundance. It is also important to recognize that current trends may not continue into the future. While current conditions appear to facilitate range expansion for gray fox, changes to New England's climate and land use may decrease gray fox occurrence in the future. Brown et al. (2018) also showed that small declines in regional occurrence probability of bird species in New England can result in large declines in the actual number of territories that a region can support. This is an important consideration, as seemingly small changes in occurrence probability may translate to much larger shifts in a species actual abundance.

Resilience of wildlife communities to change is a conservation priority for the New England region (Anderson et al., 2016). Our study focused on harvested species and provides a foundation for evaluating areas of high and low resilience under regimes of change for this group of ecologically, socially, and economically important species. Other resilience studies have focused on identifying resilient areas for broader biodiversity using focal taxa (e.g., birds) or groups (e.g., rare species). For example, Anderson et al. (2014) estimated resilience to climate change in northeastern North America using locations of rare species populations and representative natural communities as measures of biodiversity. Our study complements this and other assessments in the region (e.g., Staying Connected Initiative; Smith, Glennon, Karasin, Reed, & Kretser, 2012) by providing fine-scale information on harvested species that have been largely excluded in regional analyses.

3.6. Acknowledgments

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3.8. Tables

Table 3.1. Species distribution models (SDMs) used to map distributions for 10 wildlife species and estimate changes in distribution across the New England region of the northeastern United States. Models were developed using expert-opinion data and generalized linear mixed modeling. Models include random-effects, noted in parentheses, and scaled fixed-effect variables. See Table 3.2 for descriptions of model variables. For details on model development and parameter estimates, see Pearman-Gillman et al. (2020).

Species	Model formula
American black bear	Mean ~ prop_mature_forest + prop_all_roads + prop_forest_5k + mean_annual_precip_mm_5k + prop_fagugran_5k + (1 | State) + (1 | Expert) + (1 | Site)
Bobcat	Mean ~ prop_developed + prop_forest_edge + prop_agriculture + (1 | Expert) + (1 | Site)
Coyote	Mean ~ prop_waterbodies + prop_forest_edge + prop_major_roads_3k + prop_wetland_3k + prop_agriculture + (1 | Expert) + (1 | Site)
Gray fox	Mean ~ prop_forest_edge + prop_agriculture_3k + mean_DEM_km + (1 | State) + (1 | Expert) + (1 | Site)
Moose	Mean ~ prop_young_forest + prop_developed + prop_shrubland + mean_fall_tmax_degC + prop_forest_5k + (1 | Expert) + (1 | Site)
Raccoon	Mean ~ prop_agriculture_500m + prop_mature_forest_500m + mean_DEM_km_500m + prop_oak_500m + prop_developed_500m + (1 | Expert) + (1 | Site)
Red fox	Mean ~ prop_agriculture + prop_high_dev + mean_winter_precip_mm_3k + prop_shrubland_3k + (1 | Expert) + (1 | Site)
Striped skunk	Mean ~ mean_DEM_km_500m + prop_mature_forest_500m + prop_agriculture_500m + prop_forest_edge_500m + (1 | Expert) + (1 | Site)
White-tailed deer	Mean ~ prop_agriculture + prop_high_dev + prop_mature_forest + prop_hemlock_tamarack_cedar_3k + (1 | EcoRegion) + (1 | Expert) + (1 | Site)
Wild turkey	Mean ~ prop_decid_forest + prop_forest_edge + prop_riparian + prop_grassland_3k + (1 | EcoRegion) + (1 | Expert) + (1 | Site)

Table 3.2. Variables and associated spatial (raster) layers used in the development of wildlife species distribution models and maps across the New England region of the northeastern United States. A total of 22 fixed-effect variables and 4 random-effect variables were included in map development. The fixed-effects included 3 climate variables, 5 forest composition variables, 13 land cover variables, and 1 topographic variable. The random-effects included 2 variables (site and expert) that were included in all models and 2 candidate variables (state and eco-region). Fixed-effect variables were included at the site scale (1km) or a generalized home range scale (500m, 3km, or 5km). Spatial layers were developed for current (2010) conditions and five future (2060) scenarios: Business-As-Usual (RT), Community Connectedness (CC), Yankee Cosmopolitan (YC), Go It Alone (GA), and Growing Global (GG).

Variable	Category	Covariate name	Description	Measurement	Scale(s)	Source	
						Current	Future scenarios
Annual Precipitation	Climate	mean_annual_precip_mm	Average annual precipitation during the years 2010-2012.	Meters	5k	Duveneck & Thompson, 2019; Stoner, Hayhoe, Yang, & Wuebbles, 2013	Duveneck & Thompson, 2019; Stoner et al., 2013
Average Daily High Temperature (Fall)	Climate	mean_fall_tmax_degC	Average daily high temperature observed during the months of September, October, and November during 2010-2012.	Degrees Celsius	1k	Duveneck & Thompson, 2017; Stoner et al., 2013	Duveneck & Thompson, 2019; Stoner et al., 2013
Total Winter Precipitation	Climate	mean_winter_precip_mm	Average cumulative winter (Dec-Feb) precipitation during the years 2010-2012. Note: this measure includes all types of precipitation, not just snowfall.	Meters	3k	Duveneck & Thompson, 2017; Stoner et al., 2013	Duveneck & Thompson, 2019; Stoner et al., 2013
American Beech	Forest Composition	prop_fagugran	Forested land that is occupied by American beech (*Fagus grandifolia*).	Proportion	5k	Duveneck et al., 2015	Duveneck & Thompson, 2019; Duveneck et al., 2019
Hemlock-Tamarack-Cedar Forest	Forest Composition	prop_hemlock_tamarack_cedar	Forested land where AGB (above ground biomass) is dominated by eastern hemlock (*Tsuga canadensis*), native tamarack (*Larix laricina*), and northern white cedar (*Thuja occidentalis*).	Proportion	3k	Duveneck & Thompson, 2019	Duveneck & Thompson 2019; Duveneck et al., 2019
Mature Forest	Forest Composition	prop_mature_forest	Forested land that is classified by tree cohorts between 40 and 100 years old.	Proportion	500m, 1k	Duveneck & Thompson, 2017	Duveneck & Thompson, 2019; Duveneck et al., 2019
Oak Forest	Forest Composition	prop_oak	Forested land where AGB is dominated by white oak (*Quercus alba*), scarlet oak (*Q. coccinea*), chestnut oak (*Q. prinus*), northern red oak (*Q. rubra*), and black oak (*Q. velutina*).	Proportion	500m	Duveneck & Thompson, 2019	Duveneck & Thompson, 2019; Duveneck et al., 2019
Young Forest	Forest Composition	prop_young_forest	Forested land that is classified by tree cohorts between 20 and 39 years old.	Proportion	1k	Duveneck & Thompson, 2019	Duveneck & Thompson, 2019; Duveneck et al., 2019
Agriculture	Land Cover	prop_agriculture	Area where land cover is classified as pasture, hay, and cultivated crops.	Proportion	500m, 1k, 3k	National Land Cover Database (NLCD 2011; U.S. Geological Survey, 2014)	Thompson et al., 2019
Deciduous Forest	Land Cover	prop_decid_forest	Area where land cover is classified as deciduous forest.	Proportion	1k	NLCD 2011	Duveneck & Thompson, 2019; Duveneck et al., 2019
Developed	Land Cover	prop_developed	Area where land cover is classified as developed open space, low intensity, medium intensity, and high intensity development.	Proportion	500m, 1k	NLCD 2011	Thompson et al., 2019
Highly Developed	Land Cover	prop_high_dev	Area where land cover is classified as medium or high intensity development.	Proportion	1k	NLCD 2011	Thompson et al., 2019
Forest	Land Cover	prop_forest	Area where land cover is classified as deciduous, evergreen, and mixed forest.	Proportion	5k	NLCD 2011	Thompson et al., 2019
Forest Edge	Land Cover	prop_forest_edge	Area classified as forest that is within 300m of non-forest land cover.	Proportion	500m, 1k	NLCD 2011	Thompson et al., 2019
Grassland	Land Cover	prop_grassland	Area where land cover is classified as grassland, herbacous, pasture, or hay.	Proportion	3k	NLCD 2011	Thompson et al., 2019
Major Roads	Land Cover	prop_major_roads	Area where land cover is classified as a major road (controlled access highways, secondary highways, or major connecting roads and ramps).	Proportion	3k	National Transportation Database (NTD 2016; U.S. Geological Survey, 2016)	NTD 2016
Roads	Land Cover	prop_all_roads	Area where land cover is classified as major roads (controlled access highways, secondary highways, or major connecting roads, ramps) or local roads (local roads, 4WD roads, private driveways).	Proportion	1k	NTD 2016	NTD 2016
Riparian	Land Cover	prop_riparian	Area where vegetation is classified as riparian.	Proportion	1k	LANDFIRE 2012 (U.S. Department of the Interior, 2012)	LANDFIRE 2012; Thompson et al., 2019
Shrubland	Land Cover	prop_shrubland	Area where land cover is classified as shrub/scrub.	Proportion	1k, 3k	NLCD 2011	NLCD 2011; Thompson et al., 2019
Water	Land Cover	prop_waterbodies	Area occupied by waterbodies; lakes, ponds, reservoirs, estuaries, swamps, and marshes.	Proportion	1k	NLCD 2011	Thompson et al., 2019
Wetland	Land Cover	prop_wetland	Area classified as woody wetlands or emergent herbaceous wetlands.	Proportion	3k	NLCD 2011	NLCD 2011; Thompson et al., 2019
State	Random Effect	State	Area classified by USA state boundaries.	-	-	MassGIS, 2018	MassGIS, 2018
Eco-Region	Random Effect	EcoRegion	Area classified by terrestrial Eco Regions.	-	-	The Nature Conservancy, 2009	The Nature Conservancy, 2009
Elevation	Topography	mean_DEM_km	Height above sea level.	Kilometers	500m, 1k	Digital Elevation Model (DEM 2017; U.S. Geological Survey 2017)	DEM 2017

Table 3.3. Species-specific summary statistics for the two primary scenario drivers, Natural Resource Planning and Innovation (NRPI, high or low) and Socio-Economic Connectedness (SEC, global or local). All statistics were calculated from distribution change maps that were averaged across scenarios with like drivers and then adjusted by each species business-as-usual (RT) baseline. Values reflect the driver's isolated impact on regional occurrence relative to the RT baseline.

Species	Driver	Minimum	Maximum	Mean	Standard deviation	Quartiles		
						25%	50%	75%
American black bear	High NRPI	-0.2541	0.2022	0.0014	0.0188	-0.0038	0.0000	0.0050
	Low NRPI	-0.3682	0.2404	0.0022	0.0356	-0.0036	0.0014	0.0129
	Local SEC	-0.1938	0.2917	0.0239	0.0347	0.0014	0.0091	0.0365
	Global SEC	-0.4977	0.1491	-0.0203	0.0448	-0.0258	-0.0040	0.0005
Bobcat	High NRPI	-0.3666	0.4959	0.0042	0.0178	0.0000	0.0000	0.0078
	Low NRPI	-0.3837	0.5928	0.0021	0.0511	-0.0190	0.0031	0.0321
	Local SEC	-0.4404	0.4942	0.0103	0.0229	0.0000	0.0013	0.0159
	Global SEC	-0.3837	0.5937	-0.0041	0.0634	-0.0253	0.0047	0.0339
Coyote	High NRPI	-0.5286	0.3179	0.0003	0.0110	-0.0007	0.0000	0.0011
	Low NRPI	-0.2935	0.3748	0.0052	0.0285	-0.0076	0.0009	0.0163
	Local SEC	-0.5286	0.3256	0.0019	0.0128	0.0000	0.0000	0.0030
	Global SEC	-0.2935	0.3699	0.0035	0.0322	-0.0083	0.0014	0.0172
Gray fox	High NRPI	-0.8065	0.5664	0.0046	0.0337	-0.0023	0.0000	0.0097
	Low NRPI	-0.5491	0.6442	0.0606	0.1442	-0.0358	0.0127	0.1776
	Local SEC	-0.8074	0.5714	0.0081	0.0433	0.0000	0.0004	0.0185
	Global SEC	-0.5505	0.6441	0.0571	0.1521	-0.0427	0.0162	0.1817
Moose	High NRPI	-0.9338	0.3746	-0.0035	0.0606	-0.0055	0.0013	0.0186
	Low NRPI	-0.9375	0.7802	0.1465	0.1529	0.0110	0.0992	0.2442
	Local SEC	-0.9343	0.6268	0.1088	0.1080	0.0120	0.0795	0.1823
	Global SEC	-0.9371	0.5295	0.0342	0.0915	-0.0025	0.0047	0.0767
Raccoon	High NRPI	-0.4653	0.2528	-0.0003	0.0150	-0.0060	0.0000	0.0062
	Low NRPI	-0.3289	0.2935	0.0108	0.0223	-0.0001	0.0072	0.0221
	Local SEC	-0.2937	0.2193	-0.0016	0.0170	-0.0094	-0.0006	0.0063
	Global SEC	-0.4657	0.2588	0.0121	0.0212	0.0002	0.0090	0.0229
Red fox	High NRPI	-0.3401	0.5809	0.0001	0.0075	-0.0001	0.0000	0.0012
	Low NRPI	-0.3123	0.5809	0.0009	0.0166	-0.0005	0.0000	0.0063
	Local SEC	-0.3023	0.5809	-0.0004	0.0064	-0.0001	0.0000	0.0008
	Global SEC	-0.3401	0.5809	0.0014	0.0188	-0.0005	0.0000	0.0072
Striped skunk	High NRPI	-0.3073	0.4228	0.0014	0.0133	-0.0027	0.0008	0.0065
	Low NRPI	-0.3477	0.3436	0.0196	0.0288	0.0001	0.0113	0.0338
	Local SEC	-0.3073	0.3076	0.0018	0.0160	-0.0024	0.0021	0.0090
	Global SEC	-0.3438	0.3787	0.0191	0.0282	0.0000	0.0114	0.0337
White-tailed deer	High NRPI	-0.5648	0.7546	-0.0058	0.0278	-0.0079	-0.0013	0.0034
	Low NRPI	-0.5312	0.8336	-0.0320	0.0532	-0.0391	-0.0182	-0.0038
	Local SEC	-0.4179	0.8509	-0.0164	0.0253	-0.0258	-0.0126	-0.0022
	Global SEC	-0.5797	0.7501	-0.0214	0.0590	-0.0176	-0.0042	0.0033
Wild turkey	High NRPI	-0.5709	0.4309	0.0016	0.0218	-0.0094	0.0008	0.0120
	Low NRPI	-0.3772	0.5091	0.0302	0.0776	-0.0224	0.0098	0.0786
	Local SEC	-0.6073	0.4148	0.0080	0.0284	-0.0048	0.0079	0.0231
	Global SEC	-0.3779	0.4952	0.0237	0.0792	-0.0308	0.0043	0.0749

Table 3.4. Driver comparison statistics showing absolute difference between regional average occurrence for high vs. low NRPI (Natural Resource Planning and Innovation) and local vs. global SEC (Socio-Economic Connectedness). Values provide a quantified comparison between the NRPI and SEC drivers and indicate which driver has a greater impact on distribution change on a species-by-species basis.

Species	**NRPI Effect**	**SEC Effect**
American black bear	0.0008	0.0493
Bobcat	0.0021	0.0144
Coyote	0.0049	0.0016
Gray fox	0.0655	0.0655
Moose	0.1500	0.0746
Raccoon	0.0111	0.0137
Red fox	0.0008	0.0018
Striped skunk	0.0182	0.0173
White-tailed deer	0.0261	0.0061
Wild turkey	0.0251	0.0115

3.9. Figures

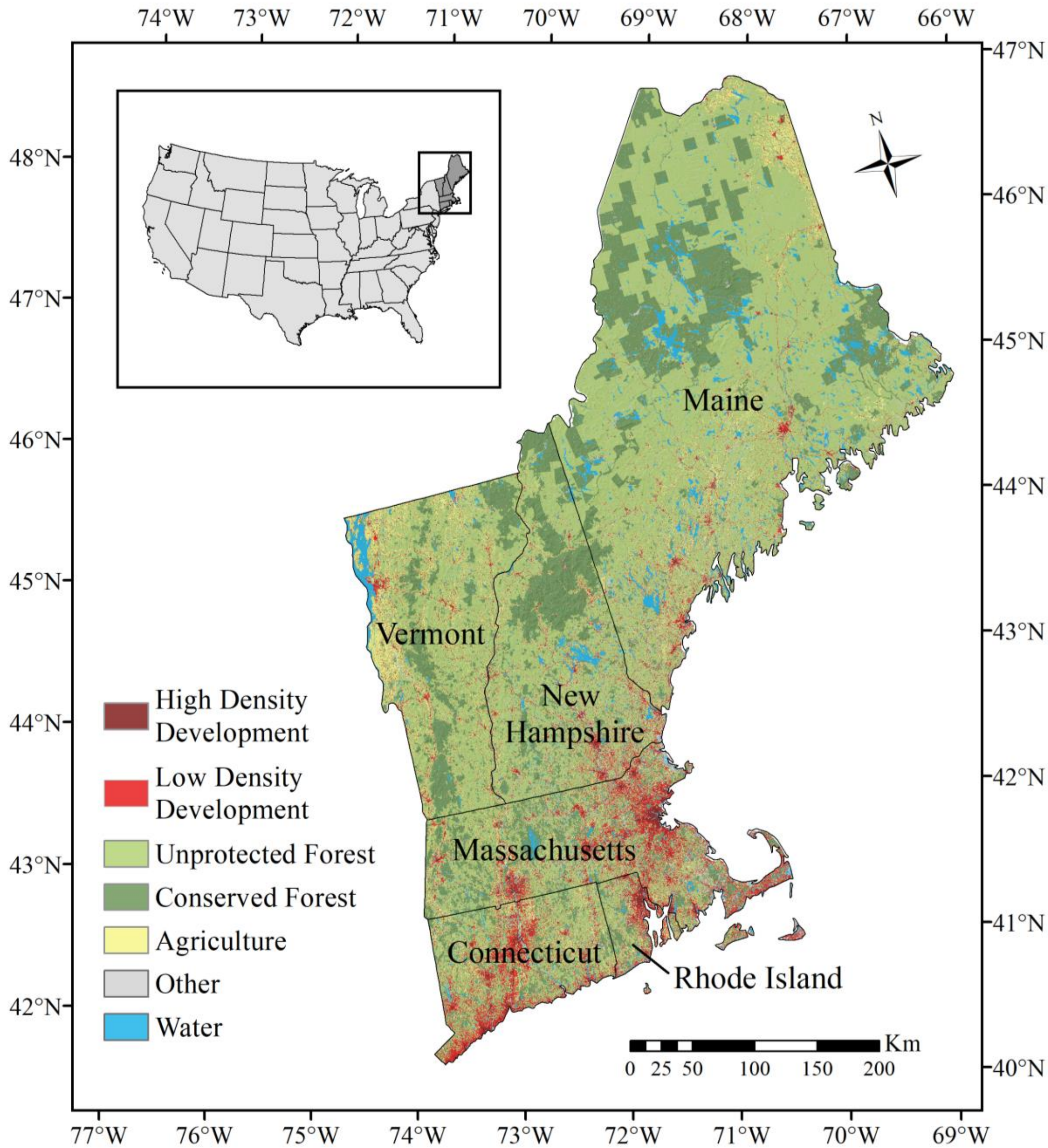

Figure 3.1. Map of the study region located in the northeastern United States. The study region included the six New England states: Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont.

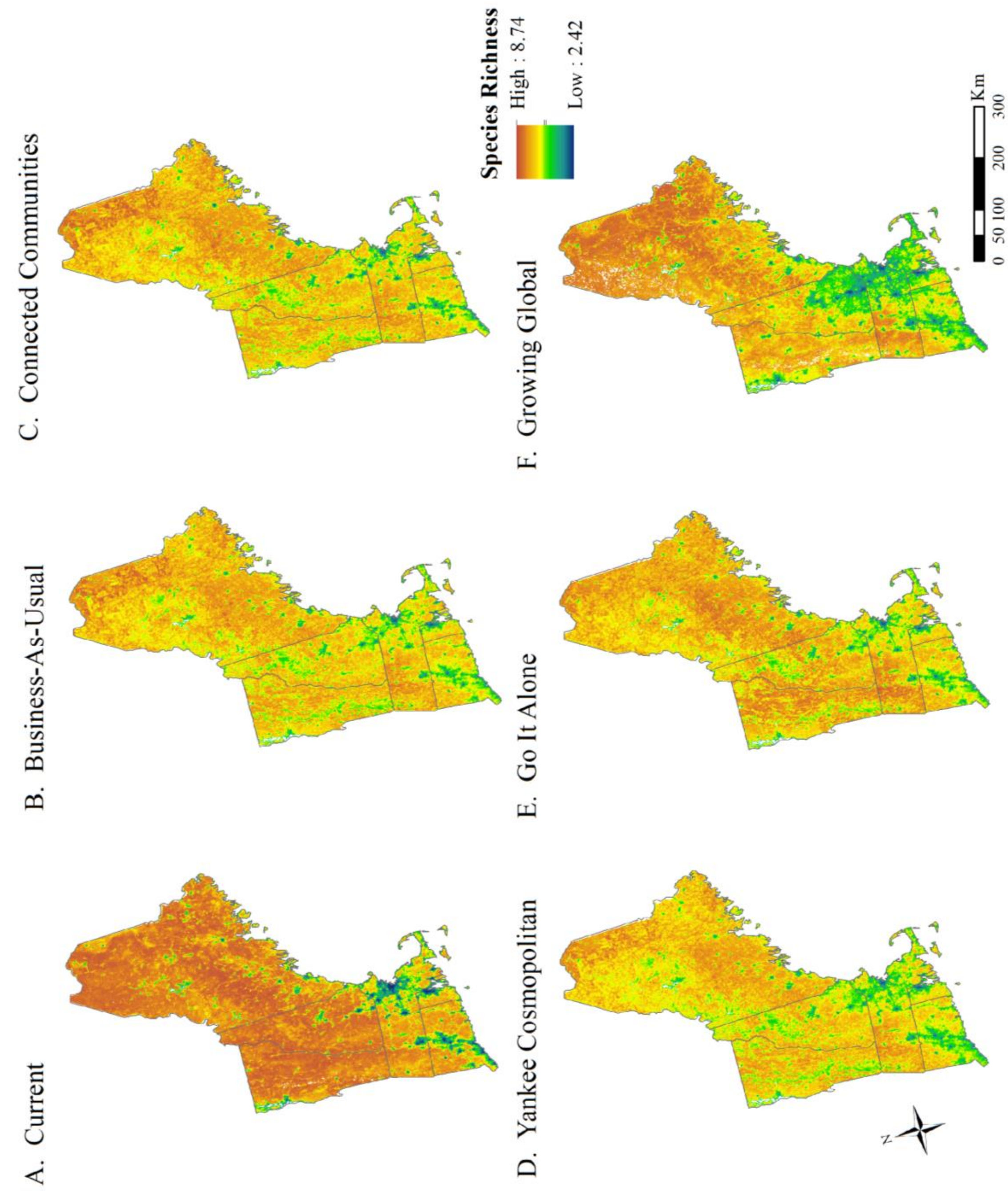

Figure 3.2. Focal wildlife species richness across New England as projected by A) current (2010) conditions, and each of the NELFP scenarios at year 2060: B) Business-As-Usual, C) Connected Communities, D) Yankee Cosmopolitan, E) Go It Alone, and F) Growing Global.

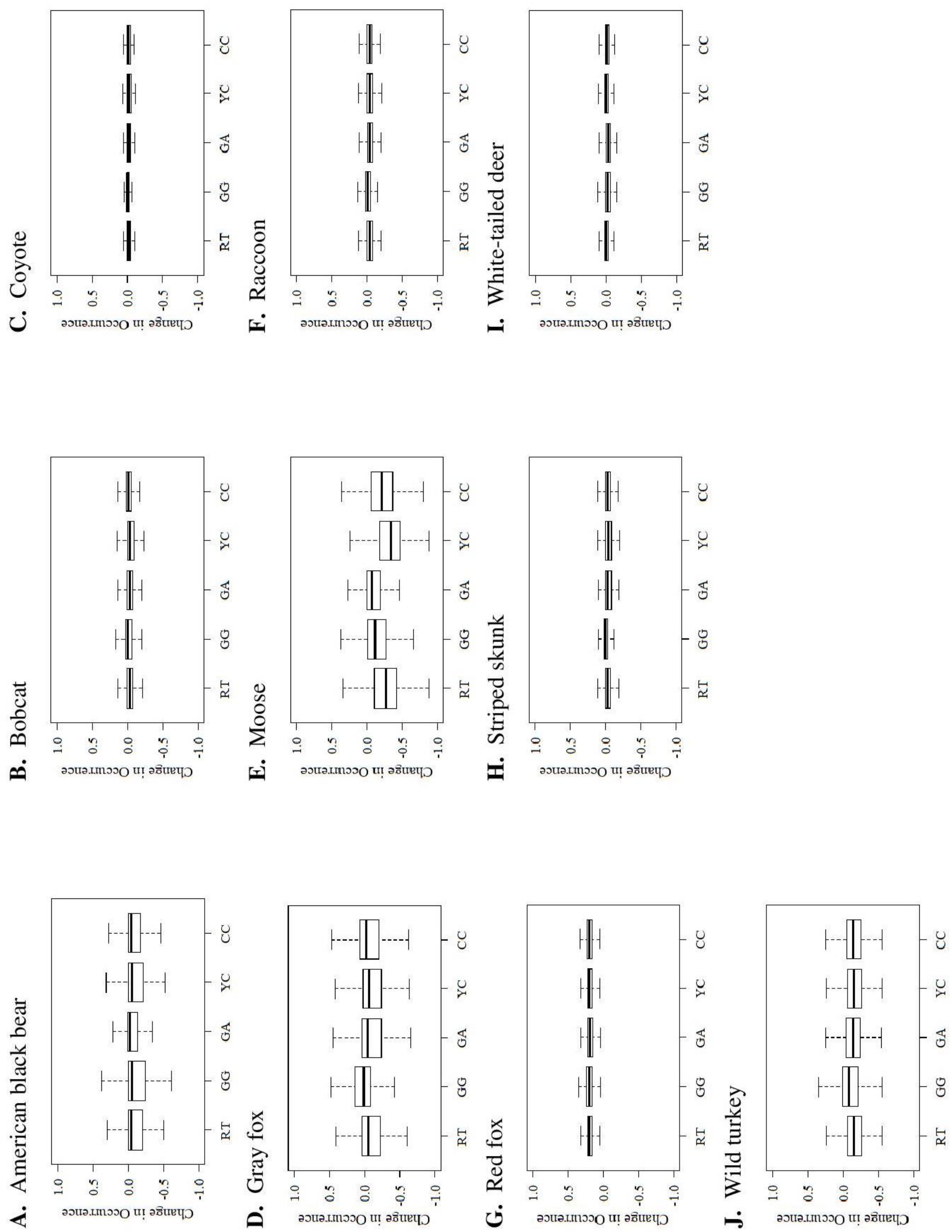

Figure 3.3. Boxplots displaying estimated changes in species occurrence likelihoods throughout the New England region of the northeastern United States. Changes in occurrence were projected by comparing species recent (2010) distribution against the year 2060 distribution projections for each NELFP scenario: Business-As-Usual (RT), Connected Communities (CC), Yankee Cosmopolitan (YC), Go It Alone (GA), and Growing Global (GG).

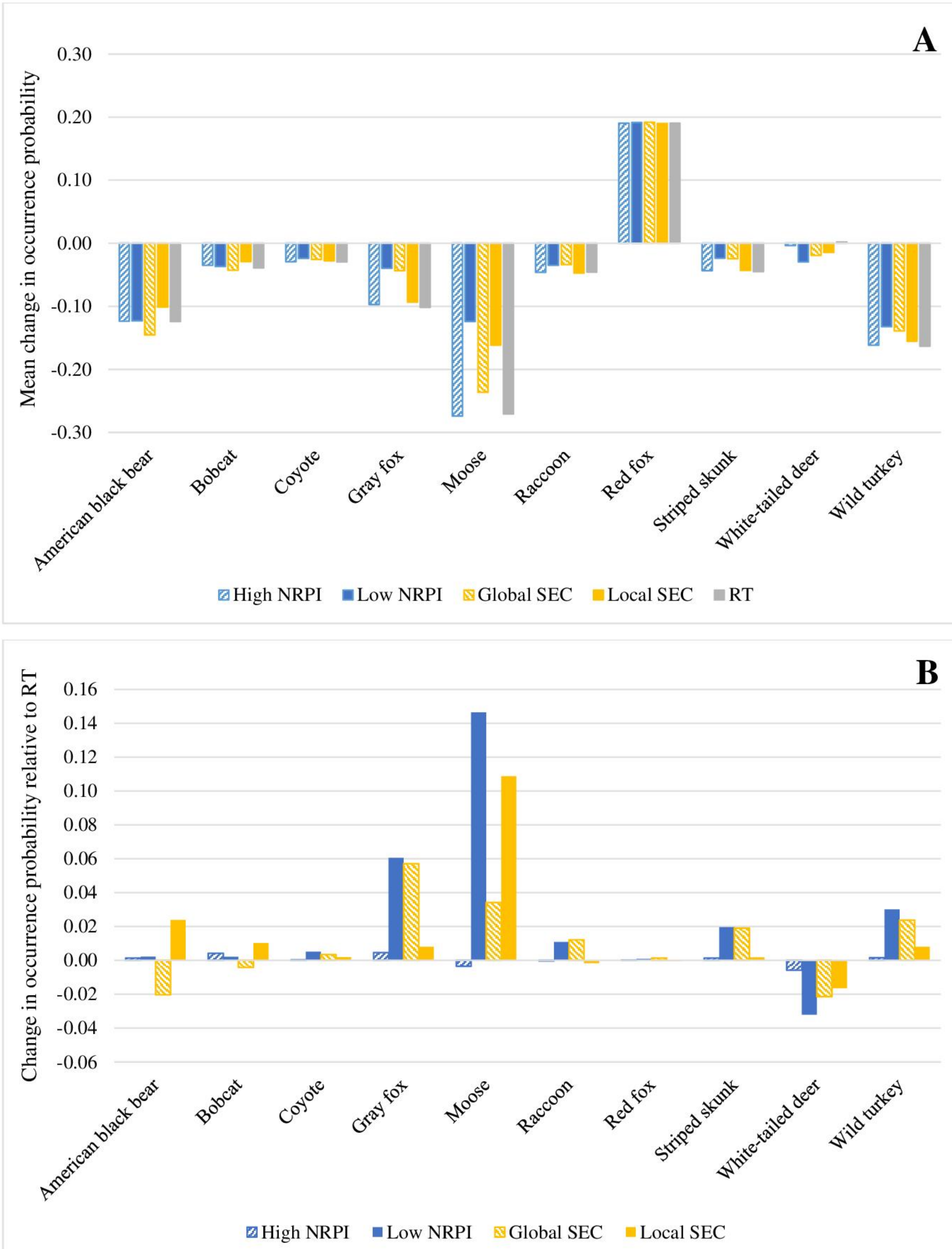

Figure 3.4. Bar graphs showing the overall impact of drivers on mean regional change in species probability of occurrence (A) and drivers isolated impact on occurrence likelihood after RT adjustment (B). For (A), values represent mean distribution change calculated from species probability of occurrence maps averaged across scenarios with like drivers. For (B), values indicate difference from the RT baseline associated with each isolated driver (i.e., High NRPI, Low NRPI, Global SEC, and Local SEC).

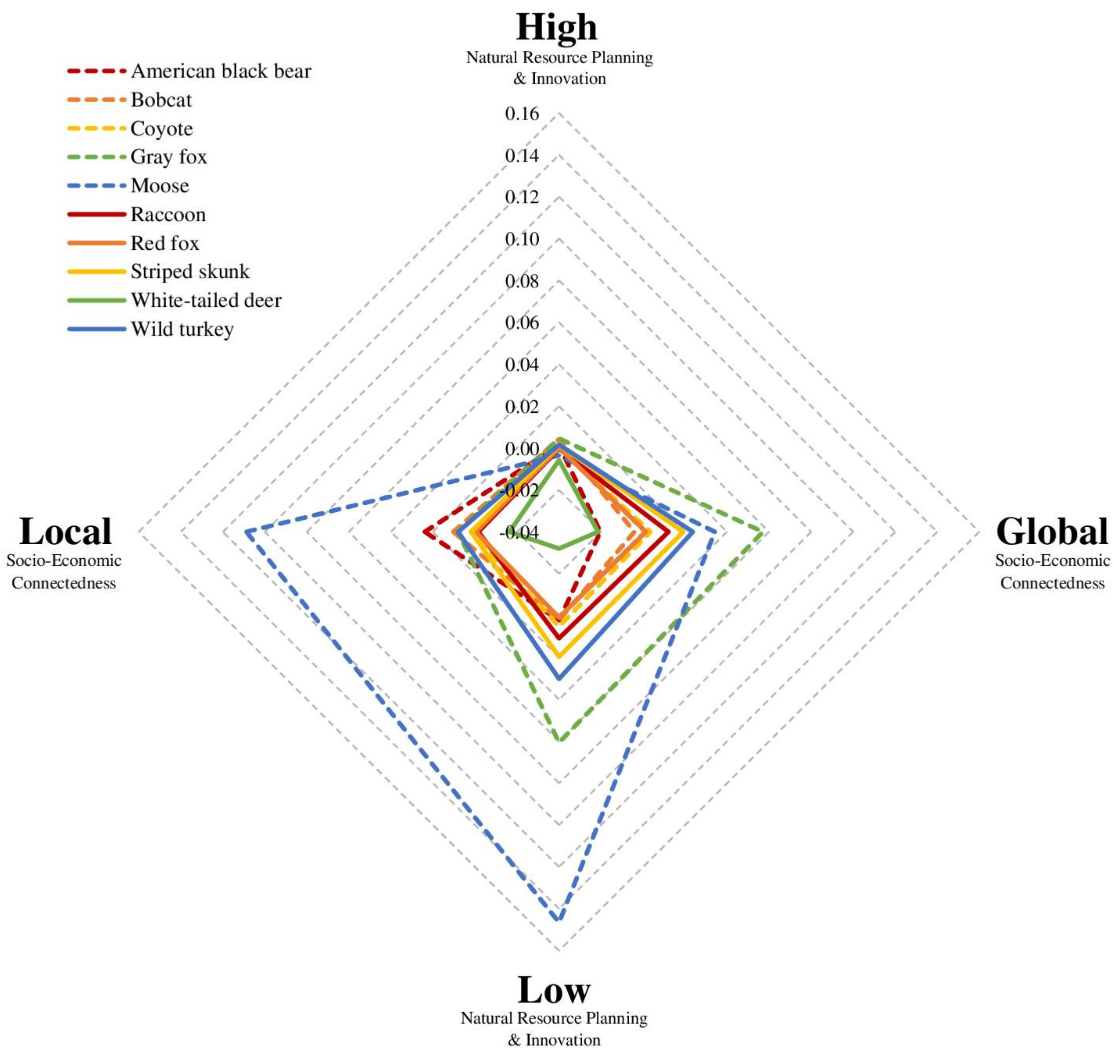

Figure 3.5. Radar plot showing species-specific (n = 10) distribution changes associated with each directional driver – i.e., high or low Natural Resource Planning and Innovation (NRPI), and global or local Socio-Economic Connectedness (SEC). The NRPI and SEC axes display how each driver impacted distribution change (i.e., change in mean regional occurrence likelihood) in the New England region of the northeastern United States between 2010 to 2060. All values were derived from species distribution models and provide a measure of how each driver shifted species regional occurrence likelihood relative to the occurrence likelihood simulated for recent trends. The overlay of all species shows driver associated trends within the focal group.

CHAPTER 4: WILDLIFE RESILIENCE AND PROTECTION IN A CHANGING NEW ENGLAND LANDSCAPE

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4.1. Abstract

Rapid changes in climate and land use threaten the resilience of wildlife species. Understanding where species are likely to occur in the future can help identify areas of resilience and guide conservation planning. We estimated changes in species distribution patterns and spatial resilience in five future scenarios for the New England region of the northeastern United States. We present scenario-specific distribution change maps for 10 harvested wildlife species and evaluated the impacts of change for these species. We identified regions of stability and increasing or decreasing habitat suitability within each scenario, and isolated areas of greatest resilience among all future scenarios. Resilience was also evaluated relative to current land protection to identify resilience patterns in and out of Protected Areas (PAs). Generally, species distributions declined in area over the 50-year assessment period (2010-2060), with the greatest declines occurring for moose (62.4%), gray fox (26.7%), and wild turkey (24.2%). Species resilience varied considerably across the region with coyote demonstrating the highest regional resilience (59.3% of the region) and moose demonstrating the lowest (0.0008% of the region). At the state level, average focal species resilience was highest in Maine and lowest in New Hampshire. Many of the focal species showed high overlap in resilience and land protection. Coyote, black bear, and white-tailed deer had the highest representation of resilience within PAs, while gray fox and wild turkey had the largest proportions of their regional resilience occurring within PAs. Overall, relatively small portions of New England – ranging between 0% and 11.9% – were both protected and resilient for the focal species. Our results provide estimates of resilience that can inform conservation planning for commonly harvested species that are important ecologically, economically,

and culturally to the region. Expanding protected area coverage to include resilient areas may provide longer term benefits to these species.

Key Words: climate change, land use change, New England, protected areas, resistance, spatial resilience, wildlife.

4.2. Introduction

Resilience describes a system's broad ability to cope with disturbances without changing state (Angeler & Allen, 2016). Spatial resilience further describes a system or landscape capacity to support ecosystems and biodiversity over space and time in response to disturbance (Allen et al., 2016; Chambers et al., 2019; Cushman & McGarigal, 2019). Because ecosystem resilience is complex and challenging to quantify, evaluating different aspects of resilience can provide important insights and perspectives. Resistance is an inherent aspect of resilience that identifies which systems, species, or locations are least vulnerable to change in the face of disturbance (Angeler & Allen, 2016; Chambers et al., 2019; T. H. Oliver et al., 2015; Walker, Holling, Carpenter, & Kinzig, 2004). Using spatial approaches to evaluate resistance can help quantify resilience within landscapes.

Resilience studies often focus on broad concepts, such as conserving biodiversity and ecosystem function, or on specific taxa of interest (e.g., avian species), or groups of vulnerable species (e.g., endangered or climate-sensitive species) (Cushman & McGarigal, 2019; Johnstone et al., 2016; Stork et al., 2009; Sundstrom, Allen, & Barichievy, 2012; Thomas & Et, 2004). For example, Anderson et al. 2016 evaluated resilience based on the ability of a geophysical setting to sustain a diversity of species, natural communities, and ecological relationships. This approach targeted the broader preservation of biodiversity and identified sites throughout eastern North America that are likely to consistently support plants and animals over the long term despite changes to climate and landscape conditions. Other studies focus more specifically on the spatial aspects of species' stability, resilience, or vulnerability to environmental change (e.g., (Crossman, Bryan, & Summers, 2012; Karp, Ziv, Zook, Ehrlich, & Daily, 2011; T. Oliver, Roy, Hill, Brereton, & Thomas, 2010; Sirami, Brotons, & Martin, 2009; Theodoridis, Patsiou, Randin, & Conti, 2018)). These studies highlight that resilience depends on the capacity of a species or ecosystem to resist change as well as the spatial and environmental context in which that system or species exists.

The New England region in the northeastern United States (186,458 km^2; Fig 4.1) covers six states and has a long history of social, economic, and ecological change (Dupigny-Giroux et al., 2018; Jeon et al., 2014; Thompson et al., 2013). With the escalating pressures of population expansion, changing land use and development, climate change, and altered disturbance regimes, New England is subject to rapid modification over the next half-century (Dupigny-Giroux et al., 2018; Duveneck & Thompson, 2019; Olofsson et al., 2016; Thompson et al., 2017; White et al., 2009). These environmental changes can significantly alter the quality, availability, and connectivity of natural systems, and subsequently influence the distribution of wildlife species (Laliberte & Ripple, 2004; Parmesan & Yohe, 2003; Root et al., 2003). Harvested species are of interest in New England because of their ecological, economic, and cultural importance (Perschel et al., 2014).

Effective long-term conservation and management of wildlife species requires a comprehensive understanding of species' potential responses not only to environmental stressors and disturbances, but also to future policy and management actions (Chambers et al., 2019). Scenario-planning methods provide a powerful way to explore and understand hypothetical futures while explicitly acknowledging their inherent uncertainty (McBride et al., 2017; G. D. Peterson et al., 2003). By exploring possible futures, scenario-planning can help address uncertainty around social drivers and spatial dynamics of environmental change and generate new insights about the complex, dynamic systems that impact wildlife futures (Henrichs et al., 2010; G. D. Peterson et al., 2003).

The New England Landscape Futures Project (NELFP), led by the Harvard Forest Long-Term Ecological Research program and the Scenarios, Services, and Society Research Coordination Network developed five plausible scenarios for how New England's landscape may change over fifty-years (2010 to 2060). The NELFP simulations include a recent trends scenario (i.e., "Business-As-Usual") and four alternative scenarios that were built around two drivers of social and ecological change (Fig 4.2): 1) Natural Resource Planning & Innovation (NRPI) – the extent to which the government and private sector invest in proactive land-use planning, ecosystem services, and technological advances for resource use – and 2) Socio-Economic Connectedness (SEC) – the local or global connectivity of population migration, economic markets, and climate policy (McBride et al., 2017). These scenarios provide informed spatial projections of climate, forest structure and composition, development, and agriculture, making them well suited for spatially explicit assessments of wildlife futures. A previous study by (Pearman-Gillman, Duveneck, Murdoch, & Donovan, 2020) evaluated future distributions of harvested species under the NELFP scenarios and found that predicted distribution patterns varied considerably among the scenarios. However, all scenarios projected a decline in the spatial distribution for most species. The results highlighted uncertainty around species' futures in the New England region and raise questions about species vulnerability and resistance to future change (Pearman-Gillman, Duveneck, et al., 2020).

The NELFP scenarios capture a wide range of possible future conditions and provide an opportunity to spatially quantify resilience across New England for harvested wildlife species. With current distribution patterns serving as a baseline, predicted changes in species occurrence patterns can be evaluated across scenarios to identify areas where occurrence remains high and is resistant to future change. Such analyses permit an evaluation of how well resilience is protected by the current conservation network. In New England, over 57,000 parcels – covering ~22% of the region's land area – are currently under a conserved land status (Fig 4.1) (USGS GAP, 2018). These protected areas (PAs) are geographically defined parcels usually created to conserve habitats, species diversity, natural resources, and recreational values (Bengtsson et al., 2003; Lilieholm, Meyer, Johnson, & Cronan, 2013). Because protected areas are often treated as static entities that remain in the same place for centuries (Bengtsson et al., 2003), it is essential to understand how existing land protection aligns with species future distributions and whether current reserve networks will support the resilience of multiple taxa in the future.

In the current era of rapid change, strategic land protection and proactive conservation planning will be critical for conserving natural landscapes. Decision-makers frequently prioritize conservation on the location of rare species or important natural communities (Groves, 2003), especially in the New England region. Broader approaches that shift the focus to conserving biological diversity and ecological functions, despite inevitable shifts in climate, land use, and species distributions are needed (M.G. Anderson et al., 2016; Pressey, Cabeza, Watts, Cowling, & Wilson, 2007).

We present a novel approach for assessing species resilience using a scenario-based framework. We target 10 ecologically and socio-economically relevant wildlife species and build a comprehensive understanding of how multiple landscape futures (the NEFLP scenarios) are likely to impact species resilience across a large regional extent. We apply a systematic approach to 1) Estimate distribution change under five alternative scenarios, 2) Identify areas on the landscape where resilience across each scenario is present for individual wildlife species, and 3) Evaluate trends in multi-species resilience and existing land protection.

4.3. Methods

Study Area

The study area spanned 186,458 km^2 in the northeastern United States and encompassed the six New England states: Connecticut, Rhode Island, Massachusetts, Vermont, New Hampshire, and Maine (Fig 4.1). This region is characterized by diverse topography (Pike & Thelin, 1989; U.S. Geological Survey, 2017a), climate (Gibson et al., 2002; Huntington et al., 2009), forest types (Brooks et al., 1992; Duveneck et al., 2015), and land uses (D R Foster et al., 2010; Olofsson et al., 2016). With two-thirds of the region's growing human population (ca.14,853,290) concentrated in major metropolitan areas (U.S. Census Bureau, 2019), New England is both one of the most densely populated and most forested regions in the United States. In 2010 – the start of the NELFP scenario timeline – approximately 80% of the region was covered in forest (D R Foster et al., 2010; Olofsson et al., 2016), with development (7.3% low density and 1.3%

high density), agriculture (6.4%) and water (4.6%) comprising the majority of the non-forested landscape (Homer et al., 2015; Olofsson et al., 2016).

Focal Species

We focused our analysis on 10 harvested wildlife species that occur widely throughout the New England region. This group included American black bear (*Ursus americanus*), bobcat (*Lynx rufus*), coyote (*Canis latrans*), gray fox (*Urocyon cinereoargenteus*), moose (*Alces alces*), raccoon (*Procyon lotor*), red fox (*Vulpes vulpes*), striped skunk (*Mephitis mephitis*), and white-tailed deer (*Odocoileus virginianus*), and wild turkey (*Meleagris gallopavo*). We selected harvested species because they are economically and culturally important and are largely the focus of state wildlife management programs; several harvested species also exert large ecological effects on ecosystems (Horsley et al., 2003; C. G. Jones et al., 1994; Pastor et al., 1998).

Objective 1 – Map species distribution change

***Scenario Simulations*.** We used scenarios developed by the New England Landscape Futures Project to estimate distribution change and resilience for the focal species (McBride et al., 2017; Thompson et al., 2019). The NELFP scenarios were built around two high-impact and highly uncertain drivers of landscape change: 1) Natural Resource Planning & Innovation (NRPI) – i.e., the extent to which the government and private sector invest in proactive land-use planning, ecosystem services, and technological advances for resource use, primarily land, energy, and water – and 2) Socio-Economic Connectedness (SEC) – i.e., the local or global connectivity of population migration, culture, economic markets, trade policy, goods and services, and climate policy (McBride et al., 2017). These drivers combine to form four plausible alternatives to recent trends for how the New England region may change over a fifty-year time period (2010 to 2060; Fig 4.2). The NELFP scenarios included: “Connected Communities” (based on high NRPI and local SEC), “Yankee Cosmopolitan” (high NRPI and global SEC), “Go It Alone” (low NRPI and local SEC), and “Growing Global” (low NRPI and global SEC). A “Business-As-Usual” scenario was also included to provide a baseline projection based on recent trends. This scenario represents a linear continuation of the land use and land cover changes observed between 1990 and 2010 (as defined by (Thompson et al., 2017)).

Each NELFP scenario followed a different trajectory of land cover and land-use change derived from the scenarios unique narrative (see (McBride et al., 2017; Thompson et al., 2019) for detailed scenario narratives). Climate changes for each scenario stayed consistent based on the assumptions of the Representative Concentration Pathway (RCP) 8.5 emission scenario (Duveneck & Thompson, 2019; IPCC, 2013). The scenario narratives were translated into spatial patterns of change using methods described by (2017) and (2019). Briefly, these simulations were developed in two stages: first using a spatially explicit cellular land change model, Dinamica Environment for Geoprocessing Objects (Soares-Filho, Coutinho Cerqueira, & Lopes Pennachin, 2002) and second using a forest landscape succession model, LANDIS-II (Scheller et al., 2007).

We used maps of species distributions under recent conditions (2010) developed by (2020) and scenario simulated distribution maps for the year 2060 developed by (Pearman-Gillman, Duveneck, et al., 2020) to evaluate species distribution changes under alternative future conditions. These maps were based on species distribution models (SDMs) developed by (2020). Models were developed from expert opinion data and evaluated the effects of combinations of 74 variables on occurrence probability. For each of the 5 scenarios, we compared the scenario-derived distribution maps against recent conditions distribution maps to assess potential changes (i.e., percent increase or decrease) in species regional distribution. Current distribution map cells were subtracted from superimposed projected distribution map cells to calculate values of projected change. Map cells with negative distribution change values represented locations of declining species occurrence and cells with positive values represented locations of increasing occurrence. All maps were developed using the raster package (Hijmans, 2016) in the statistical computing software, R (R Core Team, 2019).

Objective 2 – Identify areas of resilience

Single Scenario Resistance. For each species and all five scenarios, we identified resistant 'high-quality' and 'low-quality' areas – i.e., map cells (30 x 30 m) with similar high (or low) occurrence probabilities in both the recent conditions map and the scenario map for 2060. Scenario-specific high-quality resistance was identified on a cell-by-cell basis using two criteria: 1) high occurrence probability ($p > 0.75$) under recent conditions, and 2) minimal change ($< \pm 0.05$) in the scenario projected probability of occurrence between 2010 and 2060. We isolated cells with both high occurrence and minimal change in occurrence, to identify sites where species occurrence is most stable (resistant to change). For each scenario and species, cells that met both resistance criteria were designated by the value 1; cells that failed to meet the resistance criteria were designated by 0. Similarly, we identified resistant low-quality areas – i.e., map cells with low occurrence probabilities in 2010 ($p < 0.25$) and minimal change ($< \pm 0.05$) in the scenario projected occurrence. For each scenario and species, cells that met both criteria were designated by the value 1; cells that failed to meet the low-quality resistance criteria were designated by 0.

From Resistance to Resiliency. We developed resilience maps for each species by identifying common areas of resistance among the five alternative scenarios. Resilience was determined by multiplying across the five scenario-specific binary resistance layers; map cells that met the resistance criteria under all five future scenarios were considered resilient and retained the value 1, while cells that failed to meet the criteria under one or more of the scenarios were converted to 0. This was done for both high-quality resistant areas and low-quality resistant areas, generating a high-value resilience map and a low-value resilience map for each species. Resilience statistics were calculated for each species and were compared across the focal group to indicate trends in species resilience within New England.

Objective 3 – Evaluate resilience and existing protection

We used species final resilience maps and information from the National Inventory of Protected Areas (USGS GAP, 2018) to evaluate the overlap between the current protected area network and each species high-value resilience map. We superimposed polygons from the Protected Areas Database of the U.S. (PAD-US version 2.0) (USGS GAP, 2018); with species resilience layers and calculated zonal statistics for each Protected Area polygon in the New England region. We evaluated patterns of resilience in and out of the protected network and identified the PAs with the greatest resilience for individual species. Resilience scores were also calculated for each protected parcel based on mean resilience across all focal species. All statistics were calculated using the statistical computing language R (R Core Team, 2019) and the Geographic Information System, ArcGIS 10 (ESRI, 2018).

4.4. Results

Objective 1 – Distribution Change

American black bear, gray fox, moose, red fox, and wild turkey were projected to have the largest spatial distribution change throughout New England (Table 4.1). For example, black bear had an average occurrence probability (across all cells on the landscape) of 0.80 in the baseline projection at year 2010; under the Recent Trends scenario, the average occurrence probability decreased to 0.67 by year 2060 (a -15.3% change; Table 4.1). On average, all but one species (red fox) were projected to decline in distribution. For black bear, gray fox, moose, and wild turkey, large localized shifts in occurrence probabilities led to moderate-to-large declines in average regional distribution (-15.32%, -17.74%, -40.92, and -22.08, respectively; see Appendix D.1 for species distribution change maps). For red fox, moderate shifts in occurrence probabilities throughout New England led to relatively large increases (29.9%) in regional distribution (Table 4.1; Appendix D.1). Scenario-specific changes in occurrence were relatively low for bobcat, coyote, raccoon, striped skunk, and white-tailed deer. For example, coyote distribution was projected to decrease slightly (< -3.5%) in all 5 future scenarios, while white-tailed deer distribution was projected to decrease slightly in some scenarios (e.g., Growing Global = -4.1%) and increase slightly in others (e.g., Recent Trends = +0.5%). For these species, localized increases and decreases in occurrence probability largely balanced out across the region, resulting in minimal change in distribution across the entire New England landscape (Table 4.1; Appendix D.1).

Scenario-specific Resistance. Stability in occurrence probabilities varied considerably among species and scenarios (Table 4.2). Scenario-specific areas of high-quality resistance (i.e., map cells with high occurrence probabilities in 2010 *and* less than ±0.05 change in occurrence probability by 2060) ranged between 0.02% of the landscape (moose; Yankee Cosmopolitan) and 79.16% of the landscape (coyote; Growing Global; Table 4.2). That is, for moose <1% of high-quality map cells were resistant to change under the Yankee Cosmopolitan scenario, while for coyote almost 80% of high-quality map cells were resistant to change under the Growing Global scenario. Species with the highest average regional resistance were coyote (73.28%) and white-tailed deer (66.16%), followed by raccoon, striped skunk, and black bear. Red fox, the only species projected to increase across all future scenarios (Table 4.1), had the lowest average resistance across the landscape (1.12%), followed by wild turkey (2.29%), gray fox (4.12%) and bobcat (7.63%), all of which were projected to decline in distribution overall (Table 4.1 and Table 4.2). In terms of the individual scenarios, the percentage of resistant cells across species averaged between 28.23% (Yankee Cosmopolitan) and 33.00% (Growing Global), although the variance in resistance among the species was quite large for each scenario (Table 4.2).

Objective 2 – Resilience

High Value. High-value regional resilience – defined as the percentage of cells in the study region that were projected to remain high-quality and resistant to change across all 5 future scenarios – was greatest for coyote (59.31%), white-tailed deer (41.30%), raccoon (39.00%), striped skunk (35.73%), and black bear (33.02%; Table 4.2). The distribution of these high-value resilient areas varied among states, which varied in geographic area (Table 4.3). For example, coyote was high-value resilient throughout much of the region, with 53.20% of the high-value resilient cells occurring in Maine, followed by 17.44% in Vermont and 12.90% in New Hampshire, both of which are geographically smaller (Table 4.3, Fig 4.3). However, average species resilience within a given state was highest for Vermont (0.72), followed by Maine (0.64; Table 4.3), meaning that 72% of cells in Vermont and 64% of cells in Maine were characterized as resilient high-value for this species. White-tailed deer was resilient throughout large portions of New England, with 56.89% of regional resilience occurring in Maine, and average within-state resilience ranging from 0.23 in Rhode Island to 0.48 in Maine. Raccoon was resilient throughout much of the lower elevation areas in the region (Fig 4.3). Within states, average resilience ranged from 0.25 in New Hampshire to 0.73 in Rhode Island, with the relative majority (42.75%) of regional raccoon resilience occurring in Maine. Striped skunk was resilient in low elevation areas throughout much of the region (Fig 4.3), with highest average resilience in Rhode Island (0.59) and Connecticut (0.52), and the relative majority (49.10%) of regional resilience occurring in Maine. American black bear was predominantly resilient in northern New England, with 84.91% of regional resilience occurring in Maine, and within-state average resilience ranging from 0.00 in Rhode Island to 0.57 in Maine.

Regional high-value resilience was lowest for moose (0.00%), followed by wild turkey (0.64%), red fox (0.96%), gray fox (1.26%), and bobcat (3.99%; Table 4.2). The high-value resilient cells for ***bobcat*** were dispersed in patches throughout the region, with both the relative majority (43.3%) of regional resilience and the highest within-state average resilience (0.12) occurring in Vermont (Table 4.3, Fig 4.3). The resilient ***gray fox*** cells occurred in small patches of Massachusetts and Vermont (Fig 4.3). Average within-state resilience was highest in Massachusetts (0.09) where 87.4% of the regional resilience occurred. The resilient ***red fox*** cells occurred in patches throughout New England (Fig 4.3). Average within-state resilience was highest in Vermont (0.03) and Maine (0.01) where 49.86% and 44.74% of regional resilience occurred, respectively. ***Wild turkey*** was resilient in small patches throughout New England, with the relative majority (36.2 %) of regional resilience occurring in Maine. Average within-state resilience was highest in Connecticut (0.02) where 18.51% of regional resilience occurred. ***Moose*** resilience was extremely low throughout New England, with resilient cells occurring in only 0.0016% of Maine.

Low Value. Approximately 19% of New England represented low-value areas for one or more species in the focal group (Appendix D.2). Low-value resilience occurred throughout the region with greatest species overlap in the major metropolitan areas of southern New England and the high elevation areas of northern New England (Appendix D.2). No part of New England was designated as low-value for all species in the focal group, and only 0.04% of the region was designated as low-value for more than half of the focal group. Moose (12.79%), gray fox (7.25%), and black bear (33.02%) had the largest amount of low-value areas throughout New England, while no low-value areas were simulated raccoon and red fox (Table 4.2).

Objective 3 – Protected Areas

New England's protected area network is currently comprised of 57,449 protected parcels – including federal, state, and municipal parcels and others managed by non-profits (e.g., The Nature Conservancy) (USGS GAP, 2018). In 2010, most of the regions protected areas (54.12%) were under public ownership (e.g., White Mountain National Forest), held as private lands under protective easements (32.45%), or were protected under non-profit ownership (11.7%) (Lilieholm et al., 2013). The size of individual PAs varied significantly, with parcels sizes ranging between 1.45E-8 km^2 and 3047.65 km^2. Protected parcels in the more rural northern portion of New England were generally larger than parcels in the southern states; with land conservation in Connecticut, Rhode Island, and Massachusetts characterized by numerous small parcels, never exceeding 40.47 km^2 (10,000 acres) (Lilieholm et al., 2013). Parcel protection also varied in land-use restrictions. For example, many PAs allowed timber harvesting but did not allow land-use change (e.g., forest to development) (Lilieholm et al., 2013). Overall, approximately 22% of the New England region was under some form of land protection (Table 4.4, column 3).

Given the size of the region and the existing protected network, only small portions of the region were both protected and resilient for individual species (Table 4.4; column 4). For example, 59.31% of the map cells in New England were classified as resilient for coyote (i.e., marginal probability of resilience = 0.5931), but only 11.88% of the resilient cells were also protected (i.e., joint probability of resilience & protection = 0.1188). Resilience of other species is even less protected under the current protected network: of the 3.99% of the region that was classified as resilient for bobcat, only 0.75% is currently protected (Table 4.4, columns 2-4).

The relationship between resilience and protection can be expressed from different points of view. The conditional probability of protection, given a species resilience, is the proportion of a species resilient cells that are also protected (Table 4.4, column 5). For most species the protected network encompassed moderate levels of the species regional resilience. That is, for all species but one (moose), between 13% and 36% of the resilient cells were also protected (Table 4.4; column 5). Conditional probability of protection (given the species resilience), was highest for wild turkey (0.3519), followed by gray fox (0.3449), black bear (0.2728), and red fox (0.2489; Table 4.4, column 5). White-tailed deer, coyote, striped skunk, raccoon, and bobcat experienced moderate-to-low levels of regional resilience protection with conditional probabilities ranging between 0.2060 and 0.1316. Moose by comparison, exhibited extremely low regional resilience and had no resilient cells occurring in PAs (Table 4.4).

The relationship between resilience and protection can also be viewed from the perspective of the protected network. Given the region's conserved cells, we can determine what proportion of the protected network is also high-value resilient for each species (Table 4.4, column 6). Resilience was well represented within the current protected network for some focal species and poorly represented for others (Table 4.4, column 6). Coyote, black bear, white-tailed deer, raccoon, and striped skunk had the highest representation of resilience in protected areas (Table 4.4, Fig 4.3). For coyote, the conditional probability of resilience occurring within protection was 0.5468 – indicating that more than half (i.e., 54.68%) of the protected maps cells in New England were designated as resilient. Black bear (0.4457), and white-tailed deer (0.3889) also had relatively high conditional probability of resilience (given protection), while moose (0.000), wild turkey (0.0103), and red fox (0.0109), had low representation of resilient cells within the protected network, thus low conditional probabilities (Table 4.4).

The relationship between species resilience and protection was also evaluated for individual PAs within the protected network. Average species resilience *within* individual PAs ranged between 0 and 1 (Fig 4.4). However, for most PAs average species resilience was either 0 or 1 – meaning that most PAs were either fully resilient (i.e., all cells in the PA were resilient for the target species) or contained zero resilient cells for a given species (Fig 4.4). For example, resilient cells for black bear were not represented in the majority (~95%) of the regions PAs; however the PAs that did contain resilience were often fully resilient (Fig 4.4). Generally, PAs that contained zero resilient cells (for a given species) represented a considerably larger percent of the regions PAs then those that were fully or partially resilient. However, for some species – including coyote, raccoon, striped skunk, and white-tailed deer – a large percentage of the regions PAs were also fully resilient, and for raccoon and striped skunk the relative majority of PAs were fully resilient.

Aggregate focal species resilience was also evaluated for individual PAs. The predominantly low representation of species resilient cells within PAs led to low aggregate resilience scores (i.e., low average focal species resilience) for most PAs (Fig 4.5). Average focal species resilience was calculated for each PA based on the total representation of resilient cells within a PA (i.e., the sum of resilient cells for the 10 focal species) and the size of the PA (i.e., the number of cells within a PA). This generated a comparable resilience score for all PAs in the protected network. The majority of the region's PAs (~81%) had resilience scores below 0.3, indicating that these PAs provided high levels of resilience protection for ≤ 3 of the 10 focal species, or lower levels of resilience protection for a larger subset of the focal group (Fig 4.5). No PAs were resilient for all focal species, and only a small portion of the PAs in New England (~5%) provided resilience protection for at least half of the focal species.

4.5. Discussion

Identifying areas of resilience for wildlife represents a conservation priority, especially in the New England region, which is experiencing rapid climate and land-use changes (Dupigny-Giroux et al., 2018; Olofsson et al., 2016; White et al., 2009). We evaluated how the distributions of 10 focal species are expected to change in response to 50-years of climate change and alternative land-use trajectories. We assessed cross-scenario trends in species resistance to identify areas where species exhibited the greatest resilience to future disturbances and analyzed how species spatial resilience aligned with the current protected area network. Our analyses provide a new approach for evaluating species spatial resilience, generate questions about the long-term success of harvested species in the New England region, and highlight the value and utility of scenario-based species resilience assessments for conservation planning.

Scenario-based Resilience

Our scenario results reinforce the belief that future changes in climate and land use will likely have variable and often negative consequences for wildlife species in the New England region. Spatial patterns in species occurrence and regional resilience varied considerably among the focal group – as is expected with focal species with diverse habitat requirements (DeGraaf & Yamasaki, 2001). Overall, species with more general habitat requirements and lower sensitivity to climate or development – including coyote, white-tailed deer, raccoon, and striped skunk – exhibited the highest levels of occurrence stability and regional resilience (Table 4.2). Alternatively, species with narrower habitat requirements and higher sensitive to landscape change, such as gray fox and wild turkey exhibited low regional resilience, meaning that few cells that were high-quality under the baseline projection remained high-quality under all 5 scenarios considered. For these low resilience species, the small number of cells that are resilient may be of high conservation value – providing high-quality habitat that is robust to future change.

Three species resilience projections merit special discussion. First, for species such as red fox and bobcat, low regional resilience does not necessarily mean these species are at risk. For example, red fox will likely occupy considerable portions of a future New England landscape (Appendix D.1). However, due to consistent climate-related increases in red fox occurrence probability, only small parts of the region were considered resilient (unchanging). In the context of this study, resilient map cells only designated locations where species have the greatest occurrence stability and highest resilience potential despite uncertain future conditions. It is important to recognize that we expect wildlife species to occur outside of these resilient areas in the future; however, due to uncertainty in climate and land use change, species are not necessarily resilient in these external areas. Second, moose exhibited extremely low cross-scenario resilience, and significant variation in scenario-specific resistance (Table 4.2). For example, under the Go It Alone scenario 14.7% of the region represented high-quality resistant areas for moose. However, under the Yankee Cosmopolitan scenario only 0.02% of the region was high-quality resistant for moose (Table 4.2). This suggests that moose will experience considerably higher levels of resilience if New England undergoes changes similar to that of the Go It Alone scenario, rather than the Yankee Cosmopolitan scenario. For species like moose, land use planning is particularly important because different futures could result in very different distribution and resilience patterns.

Implications for Conservation

With spatial heterogeneity in environmental change and species responses to change, spatially explicit approaches to management and conservation are increasingly necessary (Allen et al., 2016; Chambers et al., 2019; Cushman & McGarigal, 2019). Our approach provides spatially explicit quantitative information about species occurrence that can help guide management and land use decisions at multiple spatial and temporal scales. Because state governments typically regulate management and harvest decisions, state-level resilience statistics can help guide species management and the allocation of limited funds. Understanding which species are most resilient or vulnerable to decline within a given state can also inform state-based planning and help ensure that both state and regional conservation objectives are being met. Similarly, understanding what areas are low-value resilient for wildlife species (i.e., locations with low species occurrence that are likely to remain low occurrence in the future) may benefit state and regional management and conservation planning. Areas of consistently low-value resilience for wildlife species are unlikely sites for conservation; however, these areas may represent low impact development zones or candidate areas for investing in other resources (e.g., green energy infrastructure; Appendix D.2). Both low-value and high-value resilience maps can help decision-makers identify locations for species related conservation as well as sites potentially suited for non-wildlife related resource management, or development. Obtaining this information at a regional scale provides a basis for directing limited resources to areas where they are most beneficial to broad-scale conservation (Allen et al., 2016; Chambers et al., 2019; Holl & Aide, 2011).

Understanding which species are likely to remain well represented in the protected network and which species may become more reliant on PAs may be particularly useful information for evaluating representation and persistence targets within existing PAs, and for identifying gaps in the current network (Margules & Pressey, 2000). We found that species with higher levels of regional resilience – including coyote, black bear, white-tailed deer, raccoon, and striped skunk – were generally well represented in the protected network (Table 4.4). This means that the current protected network is likely to conserve the focal species that have the highest resilience overall (i.e., marginal probability of resilience). However, for species with lower levels of regional resilience – including moose, gray fox, red fox, and wild turkey – the conditional probability of resilience within protected areas was higher than the regional probability of resilience (Table 4.4). This signifies that protected areas may be particularly important to the future resilience of these species. For these low resilience species, the few areas that are resilient may be particularly valuable sites for conservation. By adding a species' resilient sites to the protected network, these areas may be able to host source populations that can sustain less productive areas within the region (Pulliam, 1988). While the species that appear to be robust to future change may be well protected within the current network, we need to ensure that the network also protects areas that are resilient for less robust species.

Conservation strategies for large, fragmented, and rapidly changing regions need to prioritize areas where populations are most likely to persist long-term (Cabeza &

Moilanen, 2001; Margules & Pressey, 2000). Spatial prioritization tools, such as Marxan (Ball & Possingham, 2000) and Zonation (Moilanen et al., 2012), have been developed to help identify potential reserve sites that satisfy regional conservation goals. These computational decision-support tools can guide the design of protected areas and reserve systems when complex trade-offs exist (Kujala, Whitehead, Morris, & Wintle, 2015; Taylor, Cadenhead, Lindenmayer, & Wintle, 2017). However, the successful application of these tools requires reliable information about species distributions and long-term persistence (Cabeza & Moilanen, 2001). Our tools satisfy these requirements by providing fine-scale species occurrence and resilience information in a regional context. These tools are compatible with the available spatial prioritization methods and can help guide land acquisition, restoration, and management practices.

With increasing environmental change, maintaining or improving connectivity within regional landscapes is often a conservation priority to allow for gene flow and support population growth (M.G. Anderson et al., 2016; Beier & Noss, 1998; Cushman et al., 2013). Spatial resilience maps can help identify potential pathways for connectivity among resilient areas and throughout landscapes (M.G. Anderson et al., 2016). In human-dominated landscapes, habitat connectivity can facilitate movement of individuals (and their genes), which supports larger population sizes and reduces potential isolation and related demographic and genetic consequences (Crooks & Sanjayan, 2006; Fischer & Lindenmayer, 2007; McRae, Hall, Beier, & Theobald, 2012). Through the combined utility of SDMs and alternative scenarios, our maps provide a means of identifying optimal ways to connect critical natural areas and protect resilience despite an uncertain future.

We suggest that spatially explicit species resilience tools facilitate planning by providing the ability to locate areas where conservation actions are likely to have the most significant long-term benefits for wildlife species. This study provides insight into the spatial consequences of future change for wildlife species, advances our understanding of resilience at multiple spatial and ecological scales, and can help guide reserve design and conservation actions that ensure the longevity of natural systems.

Caveats to Interpretation

Although our study provides novel information about species resilience in an uncertain future, several caveats must be described. First, resilience is a complex concept often focused on numerous ecological functions (e.g., [2,4,11,71–73]). Many studies evaluate resilience through broader conceptual methods, but here we aimed to quantify the spatial resilience of individual wildlife species. Because this approach only targets resilience at the species level, we do not directly address the complexities of ecological resilience, nor do we focus on ecosystem or species interactions. We also acknowledge that there is uncertainty in the models and parameters that simulate species occurrence, and that this approach assumes that relationships between landscape factors and occurrence will remain constant (i.e., species distributions will be driven by the same effects over time).

Second, because our focus is on maintained occurrence, maps cells were only designated as high-quality resistant if species occurrence was high in the baseline projection at year 2010 and remained relatively the same in the scenario projections (±0.05 change in probability of occurrence) at year 2060. In this approach, only map cells that simulated a change in occurrence probability less than 0.05 were considered resistant; which in some cases excluded maps cells that had high occurrence probabilities at year 2010 and year 2060. For alternative assessments, it is important to acknowledge these high occurrence areas as they provide additional information about species local and regional representation. However, for this assessment we targeted areas of both high occurrence and minimal change to identify the locations where species occurrence remains stable and is most resilient despite future change. An alternative approach to identifying resistant cells is to assess their rate of change (i.e., growth rate). For example, if a map cell had an occurrence probability of 0.85 in 2010 and a scenario forecasted occurrence probability of 0.80 in 2060, this represents a difference of -0.05 and would be considered "resistant" under our assumed methodology. However, the rate of change is -6%, which may or may not be classified as "resistant", highlighting that the resistance (and subsequently resilience) calculations and conclusions are dependent upon the mathematically assumptions used. Given our raster layers for each species and NELFP scenario (Appendix D.1), it would be straightforward for future research to apply a different approach to assessing resilience.

Third, we acknowledge that there is uncertainty in the models and parameters that simulated land-use change and forest growth for each scenario, and that New England may change in ways outside the scope of the NELFP scenarios. While we are unable to consider all possible futures, the NELFP scenarios capture relevant uncertainties about the region's future landscape conditions. The central idea of scenario-planning is to consider a variety of possible futures that include many important elements of uncertainty rather than focusing on the accurate prediction of a single outcome (G. D. Peterson et al., 2003). Our approach builds from this concept and aims to overcome uncertainty about wildlife futures by identifying areas of greatest resilience across multiple scenarios. This approach is not intended as an alternative to other resilience studies. Rather, our tools are meant to complement the work of others by providing new scenario-based perspectives and spatially explicit resilience information for individual species. Despite their limitations, these tools have considerable value and can be used alongside other resilience tools and reserve design methods to evaluate the ecological impacts of management decisions and help inform effective long-term conservation.

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4.8. Tables

Table 4.1. Distribution change statistics for 10 wildlife species in the New England region of the northeastern United States. Species mean occurrence probabilities were based on recent (2010) conditions and provide baseline distribution information for the region. Distribution change indicates the percent increase or decline in regional occurrence between species 2010 distribution and each of the NELFP scenario simulated 2060 distributions. For example, black bear occurrence probability under the recent trends projection (p = 0.67) represented a 15.3% decline in distribution from the recent conditions baseline (p = 0.80).

Species	Mean occurrence probability (2010)	Distribution change (%) in NELFP scenarios by year 2060					
		Recent Trends	Growing Global	Go It Alone	Yankee Cosmopolitan	Community Connectedness	Average
American black bear	0.80	-15.3	-19.0	-11.4	-17.0	-13.9	-15.3
Bobcat	0.67	-5.6	-5.6	-5.3	-7.1	-2.9	-5.3
Coyote	0.92	-3.1	-2.2	-3.1	-3.5	-2.6	-2.9
Gray fox	0.42	-24.0	6.2	-25.0	-26.7	-19.2	-17.7
Moose	0.52	-51.8	-28.1	-19.5	-62.4	-42.8	-40.9
Raccoon	0.87	-5.6	-2.7	-6.0	-5.7	-5.6	-5.1
Red fox	0.64	29.8	30.4	29.6	29.7	30.0	29.9
Striped skunk	0.75	-6.0	-1.2	-6.3	-6.4	-5.3	-5.0
White-tailed deer	0.89	0.5	-4.1	-2.2	0.2	-0.7	-1.3
Wild turkey	0.68	-24.0	-16.7	-22.3	-24.2	-23.2	-22.1
Average		-10.5	-4.3	-7.2	-12.3	-8.6	

Table 4.2. Resistance and resilience statistics for 10 wildlife species in New England, USA. Statistics were derived from scenario simulated distribution change maps and indicate the percent of the entire New England region that was identified as “high-quality resistant”, “low-value resilient”, and “high-value resilient”. Resistance was based on species occurrence probabilities under individual NELFP scenarios. Low and high value resilience statistics were based on species simulated occurrence for all NELFP scenarios.

Species	NELFP scenario simulated high-quality resistance (%)						High-value resilience (%)	Low-value resilience (%)
	Recent Trends	Growing Global	Go It Alone	Yankee Cosmopolitan	Connected Communities	Average		
American black bear	38.13	37.49	43.71	37.41	39.69	39.29	33.02	4.71
Bobcat	5.56	15.65	5.25	5.55	6.14	7.63	3.99	1.80
Coyote	72.58	79.16	71.53	68.89	74.26	73.28	59.31	1.10
Gray fox	3.81	5.58	3.94	3.08	4.21	4.12	1.26	7.25
Moose	2.33	12.40	14.70	0.02	6.10	7.11	0.00	12.79
Raccoon	52.96	62.34	49.38	51.87	52.35	53.78	39.00	0.00
Red fox	1.10	1.26	1.11	1.09	1.06	1.12	0.96	0.00
Striped skunk	43.12	50.38	42.73	41.50	45.80	44.71	35.73	2.39
White-tailed deer	72.35	62.15	54.63	71.44	70.24	66.16	41.30	0.43
Wild turkey	1.73	3.54	2.59	1.43	2.17	2.29	0.64	0.44
Average	29.37	33.00	28.96	28.23	30.20		21.52	3.09

Table 4.3. State-based resilience statistics for 10 wildlife species in New England, USA. Statistics were calculated from species binary resilience maps developed for the region and provide measures for 1) Mean resilience: the proportion of the state that is resilient for a species, and 2) Percent of regional resilience: the percentage of a species regional resilience that occurs within each state.

Species	Connecticut		Maine		Massachusetts		New Hampshire		Rhode Island		Vermont	
	Mean	%	Mean	%	Mean	%	Mean	%	Mean	%	Mean	%
American black bear	0.03	0.66	0.57	84.91	0.01	0.19	0.22	9.48	0.00	0.00	0.11	4.75
Bobcat	0.01	2.11	0.03	38.39	0.01	3.52	0.04	12.65	0.00	0.00	0.12	43.33
Coyote	0.54	6.81	0.64	53.20	0.41	8.63	0.53	12.90	0.36	1.02	0.72	17.44
Gray fox	0.00	0.00	0.00	0.00	0.09	87.38	0.00	0.02	0.00	0.01	0.01	12.59
Moose	0.00	0.00	0.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Raccoon	0.62	11.92	0.34	42.75	0.61	19.83	0.25	9.23	0.73	3.08	0.36	13.20
Red fox	0.00	2.23	0.01	44.74	0.00	2.54	0.00	0.58	0.00	0.05	0.03	49.86
Striped skunk	0.52	11.20	0.36	49.10	0.49	17.36	0.19	7.86	0.59	2.79	0.29	11.69
White-tailed deer	0.32	5.76	0.48	56.89	0.26	7.75	0.37	12.88	0.23	0.94	0.45	15.77
Wild turkey	0.02	18.51	0.00	36.24	0.01	26.37	0.01	12.71	0.01	2.46	0.00	3.71
Average	0.21	5.92	0.24	50.62	0.19	17.36	0.16	7.83	0.19	1.04	0.21	17.23

Table 4.4. Protected resilience statistics for 10 wildlife species in New England, USA. All statistics were calculated using species binary resilience maps developed for the region and polygons from the Protected Areas Database of the U.S. (PAD-US version 2.0) [32]. Statistics include 1) Marginal probability of resilience: the proportion of the region that is resilient for each species, 2) Marginal probability of protection: the proportion of the region that is protected, 3) Joint probability of resilience and protection: the proportion of the region that is both protected and resilient, 4) Conditional probability of protection given resilience: the proportion of each species regional resilience that is protected, and 5) Conditional probability of resilience given protection: the proportion of the protected network that is resilient for each species.

Species	Marginal probability of resilience	Marginal probability of protection	Joint probability of resilience & protection	Conditional probability of protection given resilience	Conditional probability of resilience given protection
American black bear	0.3302	0.2163	0.0901	0.2728	0.4165
Bobcat	0.0399	0.2163	0.0075	0.1873	0.0344
Coyote	0.5931	0.2163	0.1188	0.2004	0.5468
Gray fox	0.0126	0.2163	0.0043	0.3449	0.0199
Moose	0.0000	0.2163	0.0000	0.0000	0.0000
Raccoon	0.3900	0.2163	0.0514	0.1317	0.2335
Red fox	0.0096	0.2163	0.0024	0.2489	0.0109
Striped skunk	0.3573	0.2163	0.0470	0.1316	0.2200
White-tailed deer	0.4130	0.2163	0.0851	0.2060	0.3889
Wild turkey	0.0064	0.2163	0.0022	0.3519	0.0103

4.9. Figures

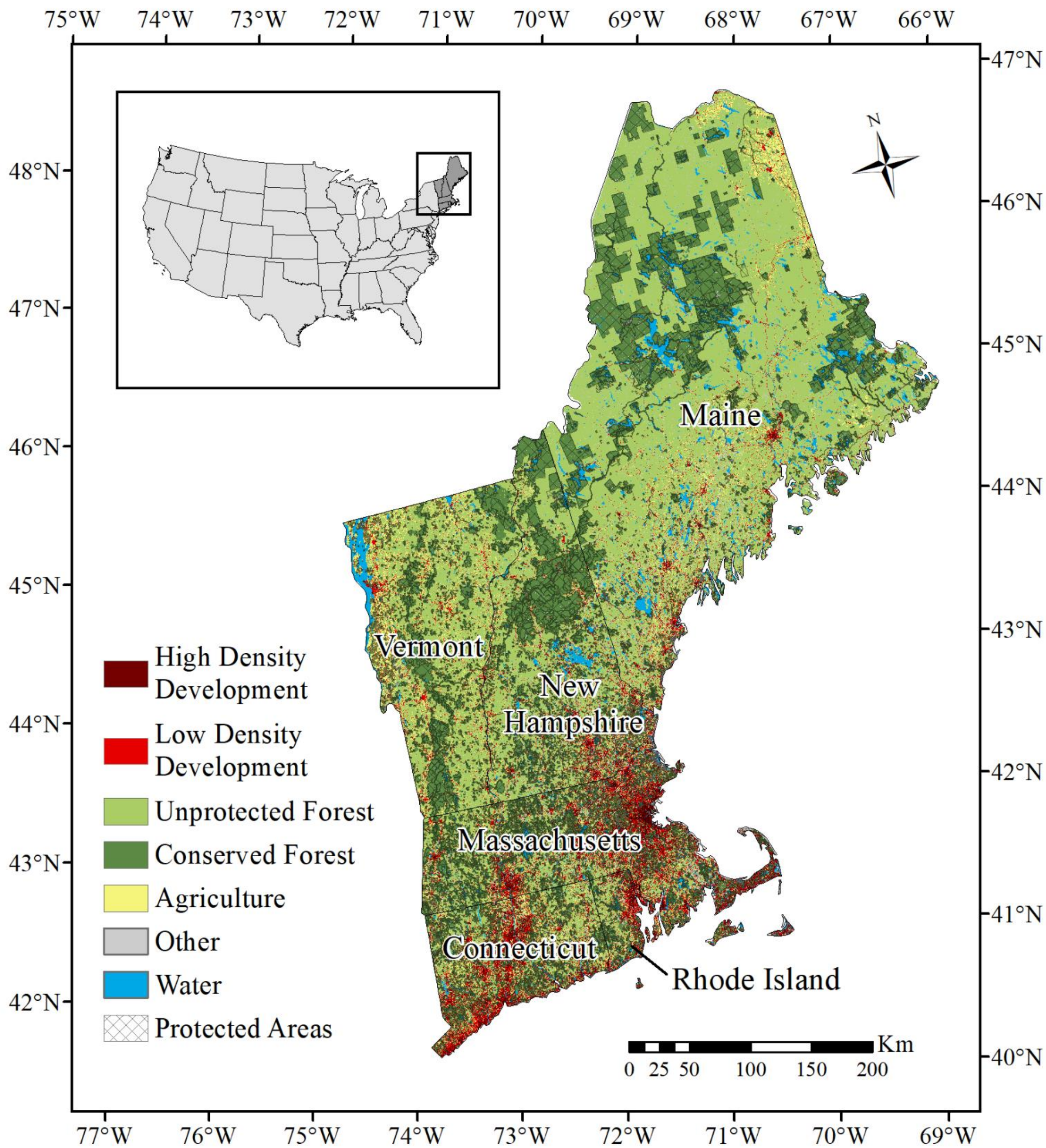

Figure 4.1. Map of the study region located in the northeastern United States. The study region included the six New England states – Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont – and over 57,000 protected area parcels.

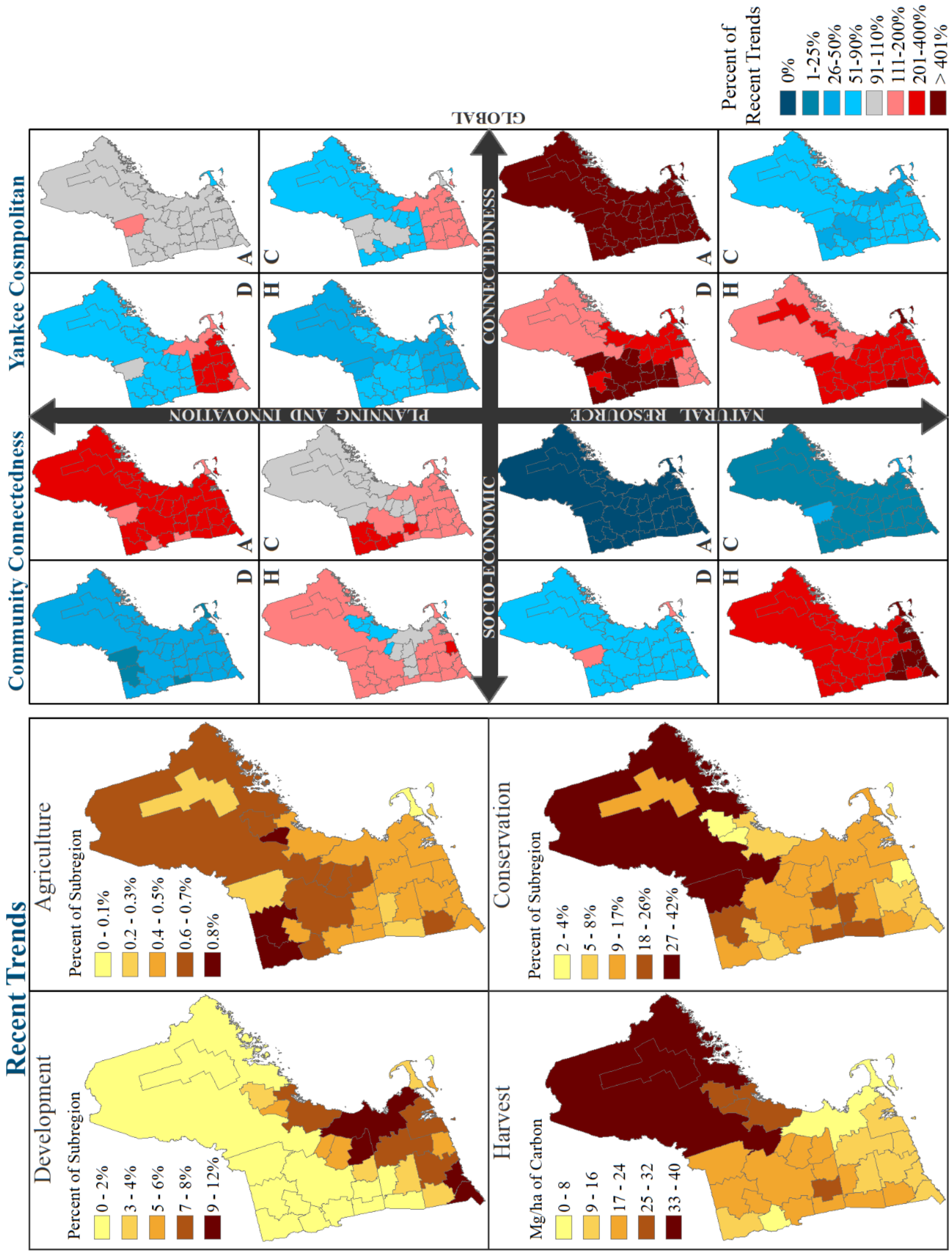

Figure 4.2. NELFP scenario matrix. Scenarios were built around two drivers of landscape change: 1) Natural Resource Planning & Innovation and 2) Socio-Economic Connectedness. The drivers form four alternatives scenarios to recent trends: “Connected Communities”, “Yankee Cosmopolitan”, “Go It Alone”, and “Growing Global”. Scenario-specific changes in development, agriculture, forest harvest, and conservation were simulated for the New England region over a fifty-year time period (2010 to 2060). Recent Trends scenario (left) displays the annual quantity of land cover and land use change broken down by subregion. The alternative NELFP scenarios (right) display the percent change from recent trends.

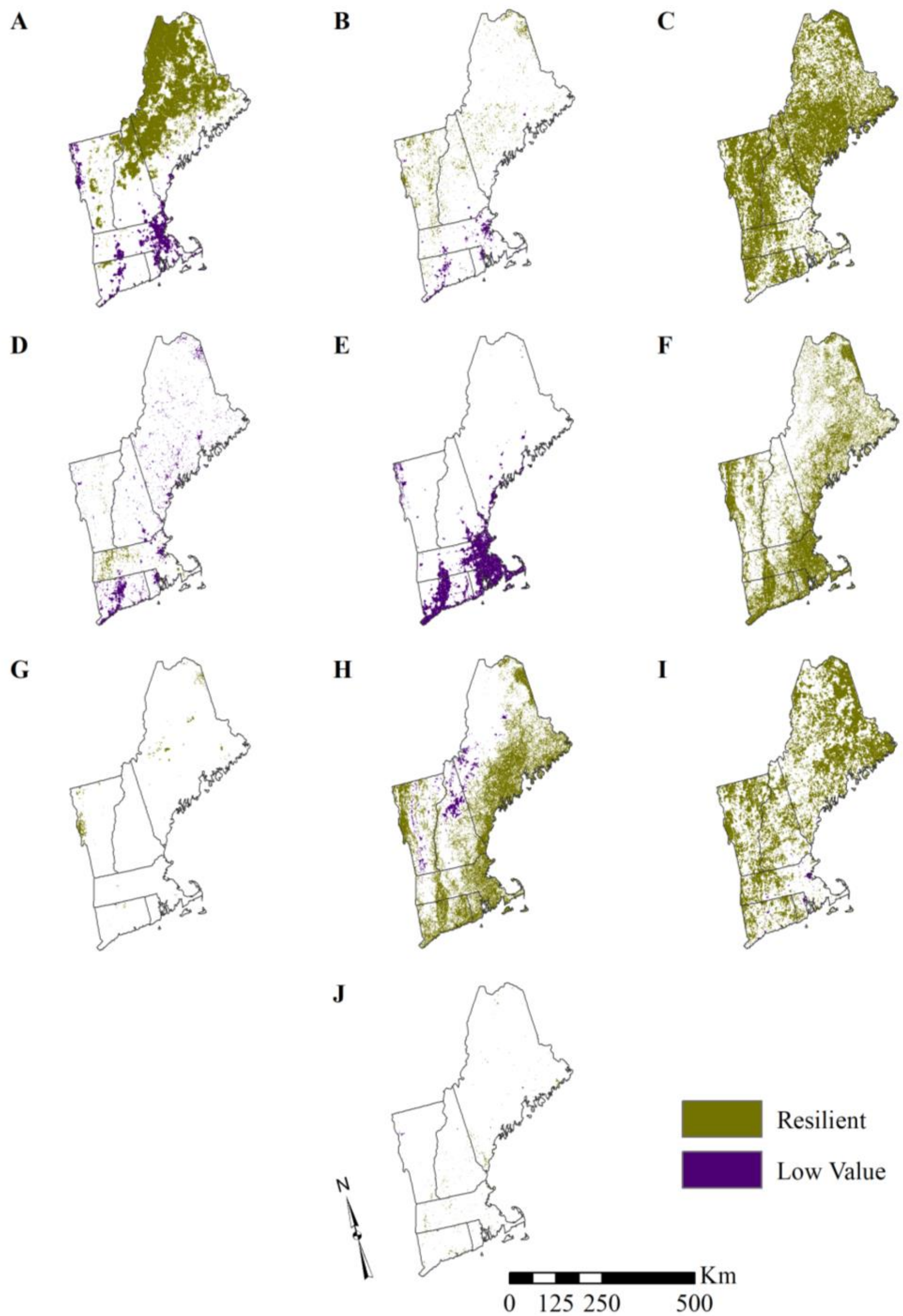

Figure 4.3. Estimated resilience for 10 wildlife species in New England, USA. Resilience was based on scenario projected distribution change between 2010 and 2060. Maps highlight areas of high and low-value resilience. Resilient cells represent the high-value resilience (i.e., areas with high occurrence probability under current conditions and across all NELFP scenarios). Low-value cells represent areas with consistently low occurrence probability under current conditions and all NELFP scenarios. Resilience maps correspond with the following species: A) American black bear, B) Bobcat, C) Coyote, D) Gray fox, E) Moose, F) Raccoon, G) Red fox, H) Striped skunk, I) White-tailed deer, and J) Wild turkey.

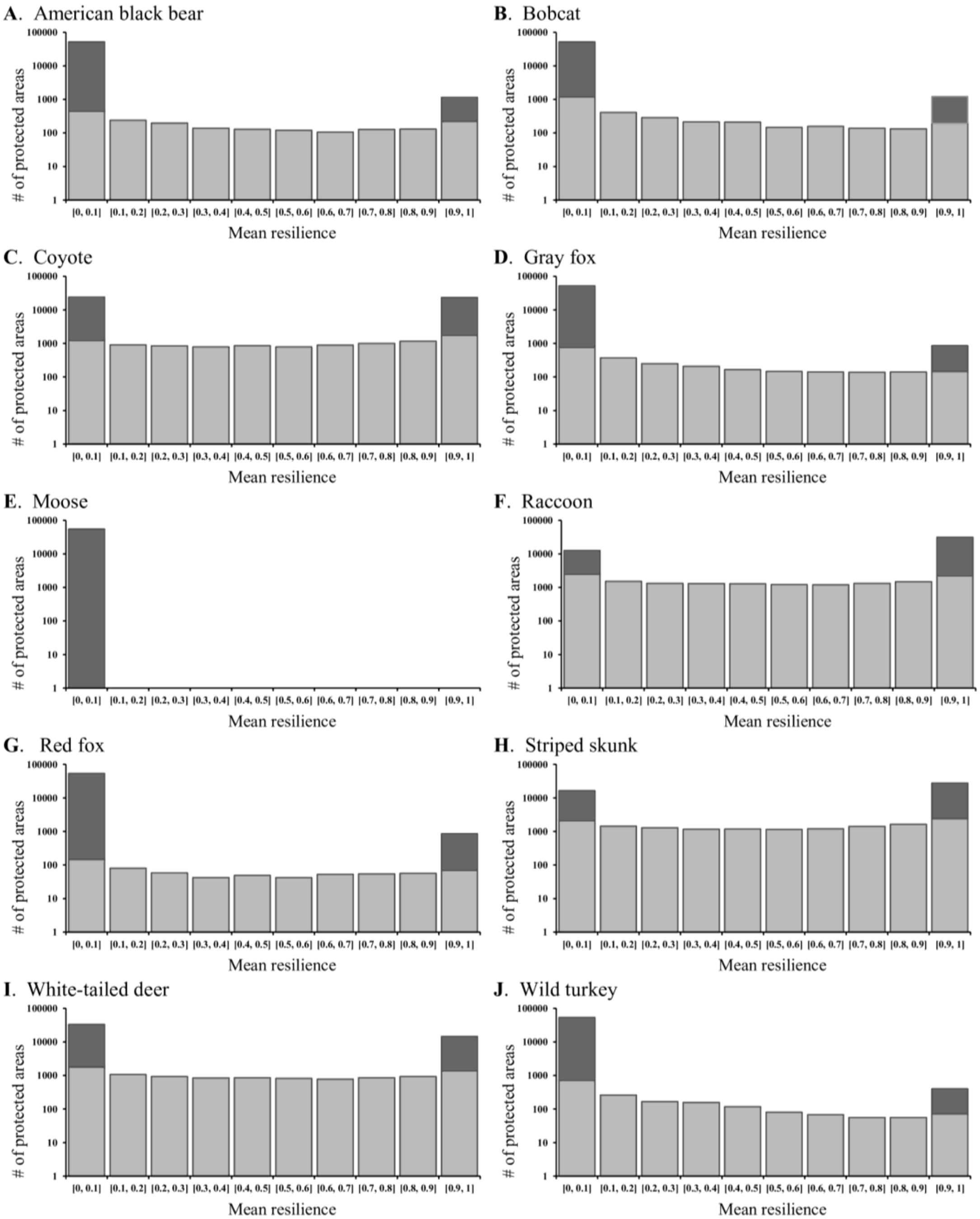

Figure 4.4. Focal species resilience within New England's protected areas. Mean resilience indicates the proportion of cells in a protected parcel that are resilient for a given species. Graphs display trends in species mean resilience within individual parcels. The dark-gray sections of the [0, 0.1] and [0.9, 1] categories indicate the number of protected parcels with a mean resilience of 0 and 1, respectively. Note the logarithmic scale of the y-axes.

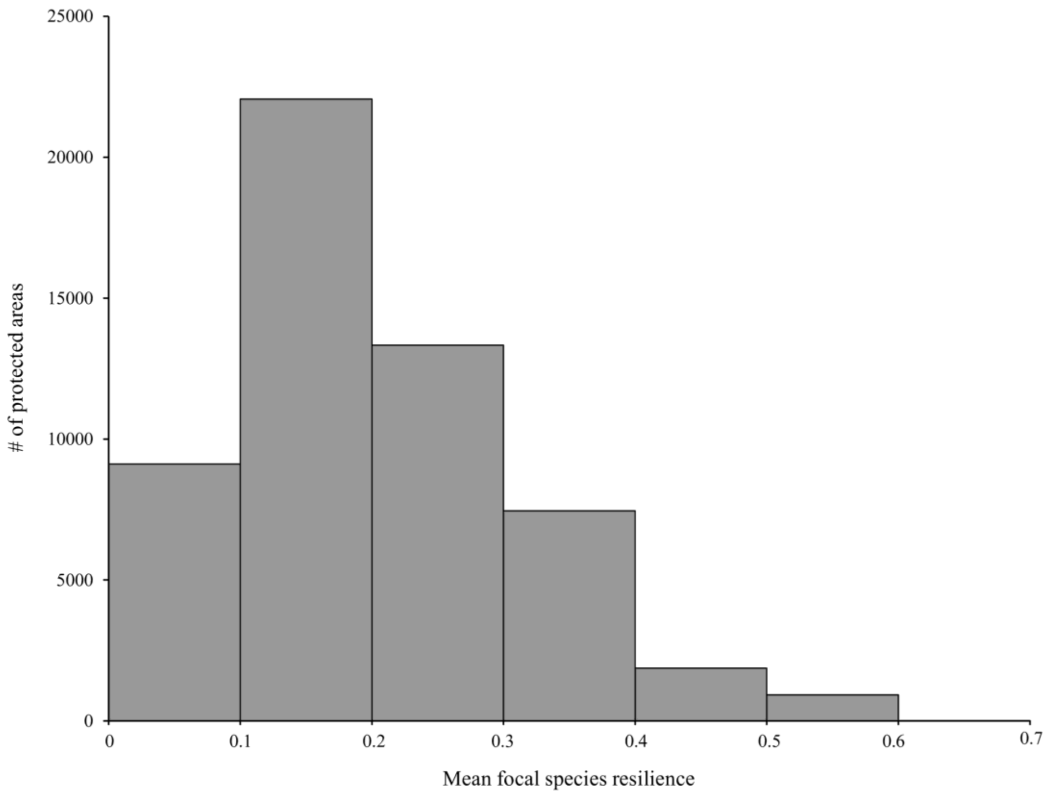

Figure 4.5. Aggregate focal species resilience within New England's protected areas. Mean focal species resilience provides a standardized indicator of resilience for each protected parcel based on aggregate focal species resilience within the parcel and the size of the parcel. Graph displays trends in average focal species resilience within individual parcels.

CHAPTER 5: SUMMARY AND CONCLUSIONS

5.1. Summary

As rates of climate and land-use change continue to accelerate worldwide, it is increasingly important to develop tools and approaches that help evaluate the consequences of future change, especially for environmental decision-making. Each chapter in this dissertation presents modeling tools and assessments that improve our understanding of wildlife futures and can help guide proactive management and conservation planning.

In Chapter 2, we developed a collection of SDMs and distribution maps that offer predictive insight about wildlife occurrence throughout New England. This study demonstrated the utility of expert elicitation and mixed modeling methods for developing SDMs and presented models for common and routinely managed wildlife species that performed well when validated against empirical data. We applied our models to the regional landscape, compared occurrence statistics among species and states throughout the region, and evaluated patterns in focal species richness. Average regional occurrence probabilities were highest for generalist species (including coyote and white-tailed deer) and lowest for species with more specific habitat constraints (including gray fox and moose). Focal species richness varied throughout the region with highest average richness occurring in the least developed states (including Vermont and Maine). This chapter laid the groundwork for Chapters 3 and 4 by providing relevant modeling tools and recent conditions distribution maps that can act as a baseline for future assessments.

Chapter 3 simulated species future distributions relative to the alternative NELFP scenarios and evaluated the drivers and consequences of future climate and land-use change for focal wildlife species. This study generally projected distribution declines for the focal wildlife throughout New England. Species distribution projections based on the recent trends scenario also generally led to greater levels of distribution decline then one or more of the alternative scenarios. These results indicate that a continuation of recent trends will negatively impact the focal wildlife. However, socio-economic factors and policy actions can shift trajectories of climate and landscape change in ways that improve the outlook for wildlife species. This chapter emphasizes the importance of considering both social and ecological drivers when addressing issues of distribution change, highlights the value of scenario-planning for understanding how various drivers and trajectories of change will influence species occurrence patterns, and provides numerous tools that can help inform spatial assessments about wildlife futures.

In Chapter 4, we implemented a novel scenario-based approach to evaluate spatial patterns in species resilience and existing land protection. This study evaluated species resilience as a function of stable occurrence probability through time and across alternative scenarios. By combining information about distribution change under the alternative NELFP scenarios, we targeted areas where species occurrence may be most stable despite uncertainty in future conditions. Species resilience varied considerably among species and throughout the region. Of the focal species, coyote had the highest simulated regional resilience while moose had the lowest simulated resilience; average resilience across all focal species was highest in Maine and lowest in New Hampshire. This study also evaluated spatial relationships between species resilience and existing land protection. Coyote, black bear, and white-tailed deer had the largest representation of resilience within protected areas, while gray fox and wild turkey had the highest proportion of their regional resilience occurring within protected areas. These results provide insight about the effectiveness of the region's current conservation network for protecting the focal wildlife species, and highlight which species are well represented within the network and which species may need additional protection in the future. Overall, this study emphasized the value of the protected network (over individual protected parcels) for the long-term conservation of wildlife species and provided tools that can support broader resilience assessments and help inform parcel selection for conservation and management objectives.

Collectively, these three studies demonstrate the utility of expert-derived SDMs and scenario-planning for evaluating wildlife futures, and advance our understanding of ecologically, economically, and culturally important wildlife species. In addition to these important scientific contributions, this work presents accessible tools that can help inform future management decisions and conservation planning throughout the New England region.

5.2. Limitations & Precautions

First, we acknowledge that there is uncertainty in the models and parameters that we used to estimate species occurrence as well as those used to simulate future climate and land cover conditions. The tools and assessments presented in this dissertation were based on the assumptions that our expert opinion data effectively captured the relationships between species occurrence and environmental factors and that these relationships will remain relatively constant over time. It is important to recognize that because the SDMs were based on current relationships, model projections do not account for potential changes in species behavior or habitat use that could emerge in the future. It is also important to note that the SDMs only include the environmental variables that were most influential on species distribution during the breeding season, and do not account for all factors that may influence distribution (e.g., species interactions). Additionally, since the SDMs were developed based on conditions and relationships observed within the New England region, they may not be representative outside of this region.

Second, our assessments of wildlife futures were built on the assumption that the NELFP scenarios effectively capture future climate and landscape conditions. We recognize that alternate future conditions are likely; however our future assessments only account for the changes represented within the NELFP scenario framework. The distribution and resilience maps presented in this body of work offer informed examples of possible future outcomes, none of the scenarios or scenario-based projection were intended as true representations of the future. Rather, the purpose of our scenario-based assessments were to improve understanding of how different environmental conditions, policy decisions, or management actions may impact wildlife species in the future.

Lastly, it is important to recognize that these assessments are only focused on 10 wildlife species. While this research targets influential wildlife species in the New England region, we recognize that many other species and factors must be considered when making conservation decisions.

5.3. Future Directions

This dissertation provides relevant and accessible tools that can be used to address additional research questions, and specific management and conservation objectives. Our SDMs and distribution maps were developed through uniform procedures and offer comparable and quantifiable information about species occurrence through time and space. These tools provide informed species occurrence estimates and offer a means of exploring the spatial consequences of management decisions and changing environmental conditions for wildlife species.

Our scenario-based assessments provide examples of how scenario-planning can offer insight about wildlife futures. In addition to these assessments, our SDMs can be applied to other scenarios or conservation design frameworks to evaluate how specific management or land-use decisions may impact wildlife within targeted areas or throughout the landscape. Preemptive scenario-based assessments can provide information about the potential outcomes of policy or land-use actions and may be particularly useful to land mangers or conservation organizations tasked with managing multiple resources.

This body of work provides a framework for developing compatible maps and modeling tools for multiple taxa and large regional extents, offers scenario-based perspectives and spatially explicit occurrence and resilience information for important harvested species in the New England region, and presents versatile tools that can be used along with other tools and methods to help inform conservation and management decisions. While the tools presented in this dissertation are best suited for assessments focused in the northeastern United States, the methods have broader application and can be implemented for different focal species and regions worldwide.

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APPENDIX A

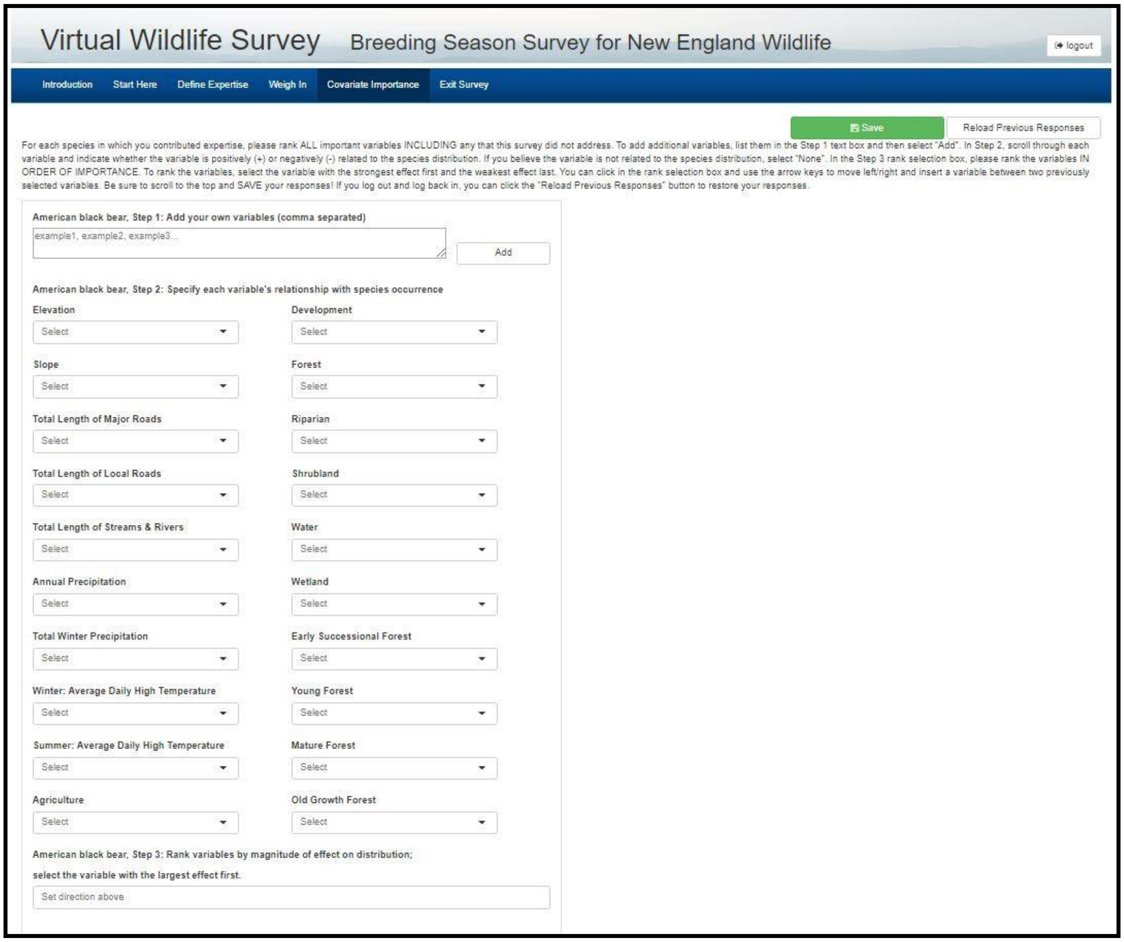
A.1. List of habitat covariates (n = 57) used in the expert elicitation survey. The covariate list included 10 general land cover variables, 37 forest composition variables, 3 topographic variables, and 4 climate variables.

Category	Variable	Description	Source
Climate	Annual Precipitation	Average annual precipitation based on 30 year normals (1981-2011).	PRISM Climate Group (PRISM 2015)
Climate	Summer: Average Daily High Temperature	Average daily high temperature observed at the site during the months of June, July and August.	PRISM 2015
Climate	Total Winter Precipitation	Average cumulative winter (December - February) precipitation based on 30 year normals (1981-2011). Note: This measure includes all types of precipitation, not just snowfall. This acts as an approximate measure for snow cover, given that temperatures are below freezing.	PRISM 2015
Climate	Winter: Average Daily High Temperature	Average daily high temperature observed at the site during the months of December, January and February.	PRISM 2015
Forest composition	American Basswood	Proportion of the forests above ground biomass (AGB) occupied by American Basswood (*Tilia americana*).	Duveneck et al. 2015
Forest composition	American Beech	Proportion of the forests AGB occupied by American Beech (Fagus grandifolia).	Duveneck et al. 2015
Forest composition	American Elm	Proportion of the forests AGB occupied by American Elm (*Ulmus americana*).	Duveneck et al. 2015
Forest composition	Balsam Fir	Proportion of the forests AGB occupied by Balsam Fir (*Abies balsamea*).	Duveneck et al. 2015
Forest composition	Balsam Poplar	Proportion of the forests AGB occupied by Balsam Poplar (*Populus balsamifera*).	Duveneck et al. 2015
Forest composition	Bigtooth Aspen	Proportion of the forests AGB occupied by Bigtooth Aspen (*Populus grandidentata*).	Duveneck et al. 2015
Forest composition	Black Ash	Proportion of the forests AGB occupied by Black Ash (*Fraxinus nigra*).	Duveneck et al. 2015
Forest composition	Black Cherry	Proportion of the forests AGB occupied by Black Cherry (*Prunus serotina*).	Duveneck et al. 2015
Forest composition	Black Oak	Proportion of the forests AGB occupied by Black Oak (*Quercus velutina*).	Duveneck et al. 2015
Forest composition	Black Spruce	Proportion of the forests AGB occupied by Black Spruce (*Picea mariana*).	Duveneck et al. 2015
Forest composition	Chestnut Oak	Proportion of the forests AGB occupied by Chestnut Oak (*Quercus prinus*).	Duveneck et al. 2015
Forest composition	Early Succession	Forested land that is classified by tree cohorts between 2 and 19 years old.	Duveneck & Thompson 2017

Forest composition	Eastern Hemlock	Proportion of the forests AGB occupied by Eastern Hemlock (*Tsuga canadensis*).	Duveneck et al. 2015
Forest composition	Eastern Hophornbeam	Proportion of the forests AGB occupied by Eastern Hophornbeam (*Ostrya virginiana*).	Duveneck et al. 2015
Forest composition	Eastern White Pine	Proportion of the forests AGB occupied by Eastern White Pine (*Pinus strobus*).	Duveneck et al. 2015
Forest composition	Gray Birch	Proportion of the forests AGB occupied by Gray Birch (*Betula populifolia*).	Duveneck et al. 2015
Forest composition	Mature Forest	Forested land that is classified by tree cohorts between 40 and 100 years old.	Duveneck & Thompson 2017
Forest composition	Northern Red Oak	Proportion of the forests AGB occupied by Northern Red Oak (*Quercus rubra*).	Duveneck et al. 2015
Forest composition	Northern White Cedar	Proportion of the forests AGB occupied by Northern White Cedar (*Thuja occidentalis*).	Duveneck et al. 2015
Forest composition	Old Growth Forest	Forested land that is classified by tree cohorts older than 100 years.	Duveneck & Thompson 2017
Forest composition	Open Space	Forested land that is classified by tree cohorts younger than a 1 year.	Duveneck & Thompson 2017
Forest composition	Paper Birch	Proportion of the forests AGB occupied by Paper Birch (*Betula papyrifera*).	Duveneck et al. 2015
Forest composition	Pignut Hickory	Proportion of the forests AGB occupied by Pignut Hickory (*Carya glabra*).	Duveneck et al. 2015
Forest composition	Pitch Pine	Proportion of the forests AGB occupied by Pitch Pine (*Pinus rigida*).	Duveneck et al. 2015
Forest composition	Quaking Aspen	Proportion of the forests AGB occupied by Quaking Aspen (*Populus tremuloides*).	Duveneck et al. 2015
Forest composition	Red Maple	Proportion of the forests AGB occupied by Red Maple (*Acer rubrum*).	Duveneck et al. 2015
Forest composition	Red Pine	Proportion of the forests AGB occupied by Red Pine (*Pinus resinosa*).	Duveneck et al. 2015
Forest composition	Red Spruce	Proportion of the forests AGB occupied by Red Spruce (*Picea rubens*).	Duveneck et al. 2015
Forest composition	Scarlet Oak	Proportion of the forests AGB occupied by Scarlet Oak (*Quercus coccinea*).	Duveneck et al. 2015
Forest composition	Sugar Maple	Proportion of the forests AGB occupied by Sugar Maple (*Acer saccharum*).	Duveneck et al. 2015
Forest composition	Sweet Birch	Proportion of the forests AGB occupied by Sweet Birch (*Betula lenta*).	Duveneck et al. 2015
Forest composition	Tamarack (native)	Proportion of the forests AGB occupied by native Tamarack (*Larix laricina*).	Duveneck et al. 2015
Forest composition	White Ash	Proportion of the forests AGB occupied by White Ash (*Fraxinus americana*).	Duveneck et al. 2015

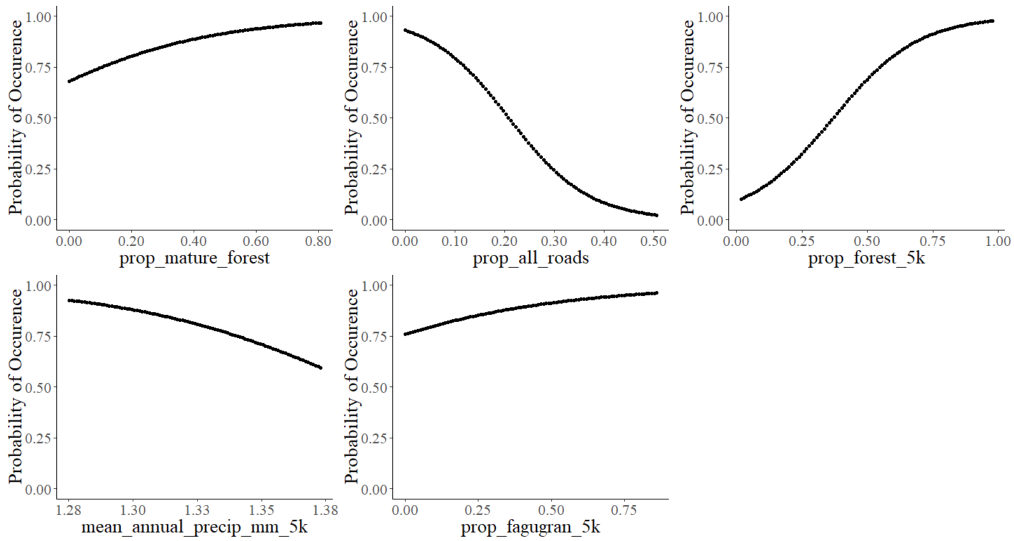
Forest composition	White Oak	Proportion of the forests AGB occupied by White Oak (*Quercus alba*).	Duveneck et al. 2015
Forest composition	White Spruce	Proportion of the forests AGB occupied by White Spruce (*Picea glauca*).	Duveneck et al. 2015
Forest composition	Yellow Birch	Proportion of the forests AGB occupied by Yellow Birch (*Betula alleghaniensis*).	Duveneck et al. 2015
Forest composition	Young Forest	Forested land that is classified by tree cohorts between 20 and 39 years old.	Duveneck & Thompson 2017
Land cover	Agriculture	Area where land cover is classified as pasture, hay and cultivated crops.	National Land Cover Database 2011 (NLCD 2011; U.S. Geological Survey 2014)
Land cover	Developed	Area where land cover is classified as developed open space, low intensity, medium intensity and high intensity development.	NLCD 2011
Land cover	Eco-Region	Terrestrial Eco Regions.	The Nature Conservancy 2009
Land cover	Forest	Area where land cover is classified as deciduous, evergreen & mixed forest.	NLCD 2011
Land cover	Riparian	Area where the Existing Vegetation Type (EVT) is classified as riparian.	LANDFIRE 2012 (U.S. Department of the Interior, 2012)
Land cover	Shrubland	Area where land cover is classified as shrub/scrub.	NLCD 2011
Land cover	Total Length of Local Roads	Combined length of all local road segments (local roads, 4WD roads, private driveways) present within the site.	National Transportation Database (NTD 2016; U.S. Geological Survey 2016)
Land cover	Total Length of Major Roads	Combined length of all major road segments (controlled access highways, secondary highways or major connecting roads, ramps) present within the site.	NTD 2016
Land cover	Total Length of Streams & Rivers	Combined length of all stream, connector and river segments present within the site.	National Hydrography Dataset (NHD 2017; U.S. Geological Survey 2017a)
Land cover	Water	Area occupied by waterbodies; lakes, ponds, reservoirs, estuaries, swamps and marshes.	NHD 2017
Land cover	Wetland	Area classified as woody wetlands or emergent herbaceous wetlands.	NLCD 2011
Topography	Aspect	Dominant cardinal or ordinal direction observed across the site.	Digital Elevation Model (DEM 2017; U.S. Geological Survey 2017)
Topography	Elevation	Average elevation throughout the site.	DEM 2017
Topography	Slope	Average slope observed throughout the site.	DEM 2017

A.2. Covariate importance ranking exercise interface: A) Step 1, text box used to add additional variables; B) Step 2, drop down boxes used to select variable directionality; C) Step 3, drop down list used to select variables in descending order of importance.

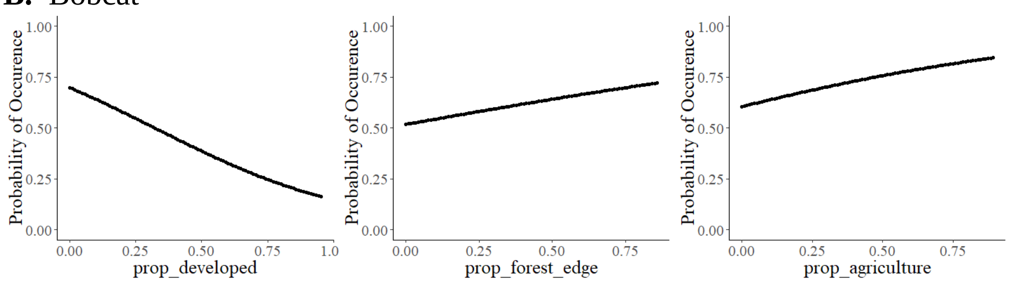


A.3. Effects of individual covariates on each species top model fitted using expert opinion data from wildlife experts in the northeastern United States and mixed-effect modeling. X-axes on plots show the model covariate values at the scale used in model fitting (see Table 2.3 for covariate descriptions); land cover (proportional cover), temperature (degrees Celsius), precipitation (mm), and elevation (km). Y-axes show the occurrence probabilities estimated from each model considering the effects of the intercept and the individual model covariate when all other covariates are set to their mean value.

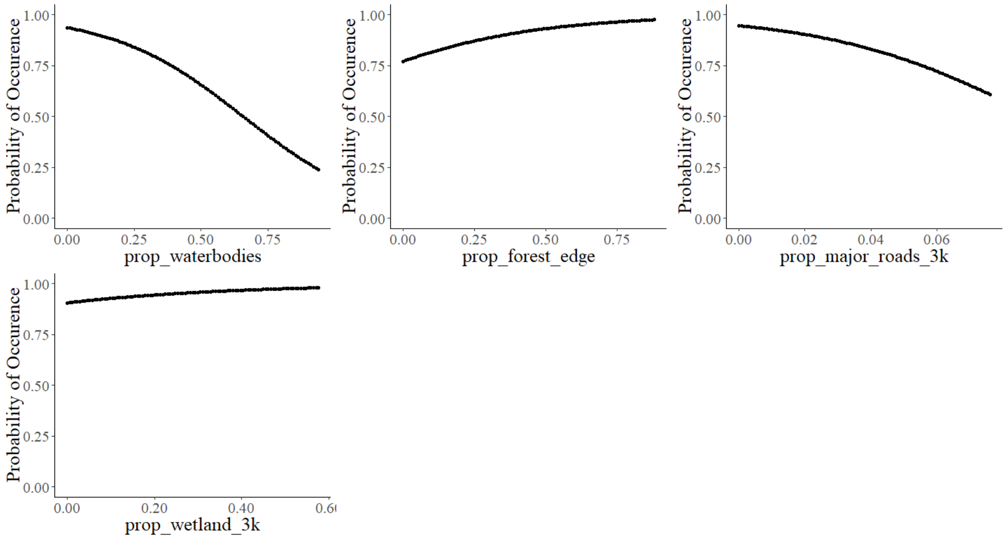
A. American black bear



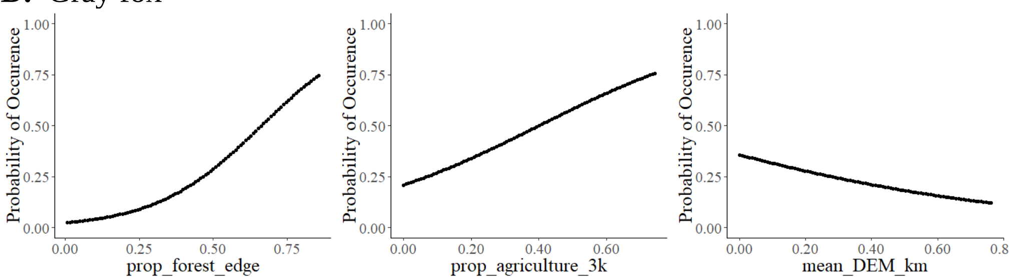
B. Bobcat



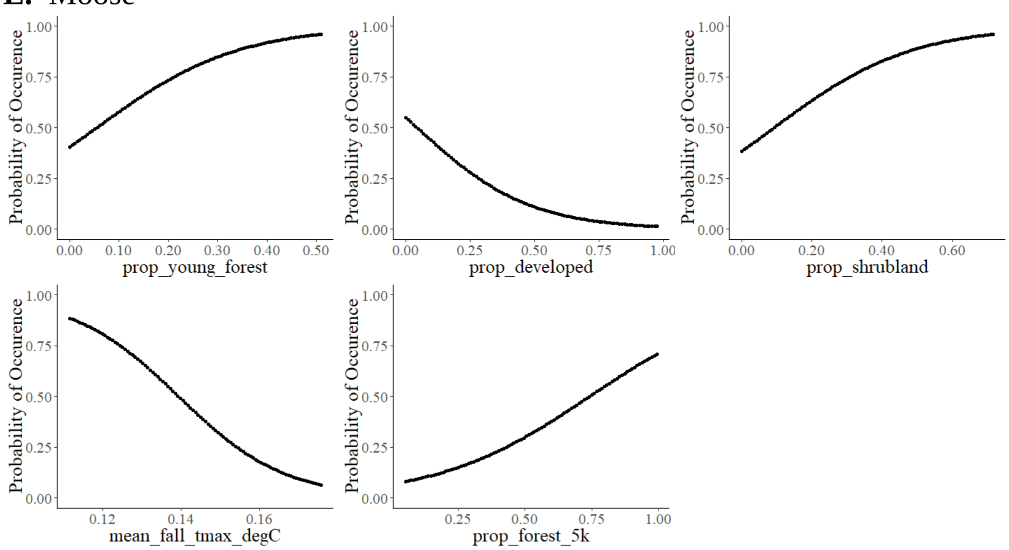
C. Coyote



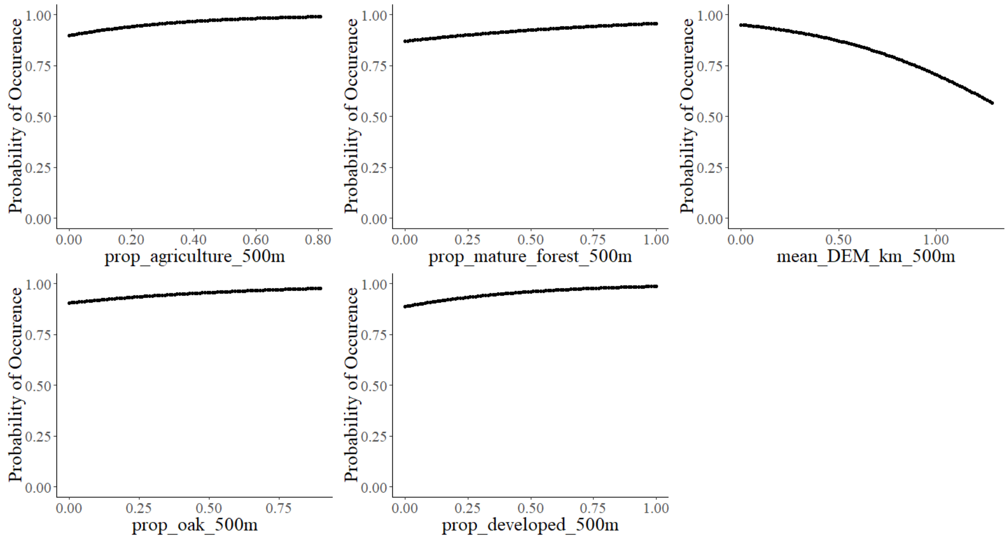
D. Gray fox



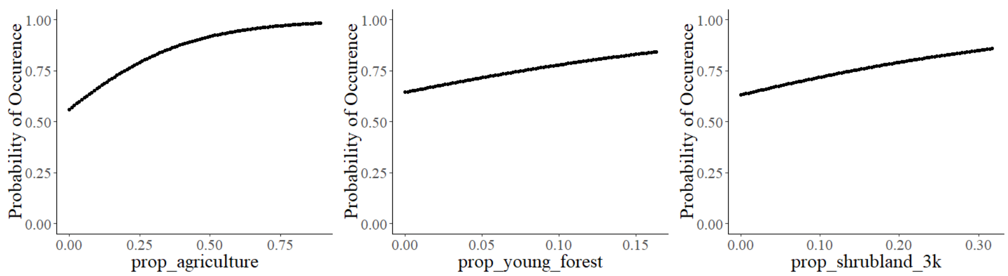
E. Moose



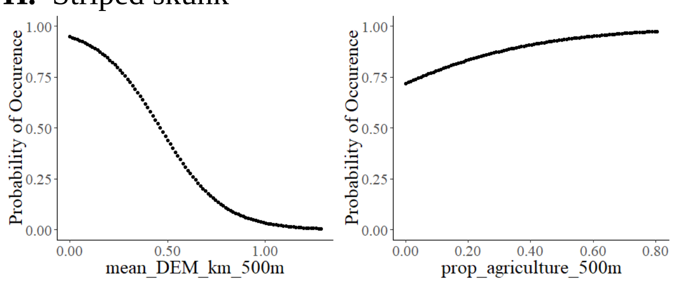
F. Raccoon



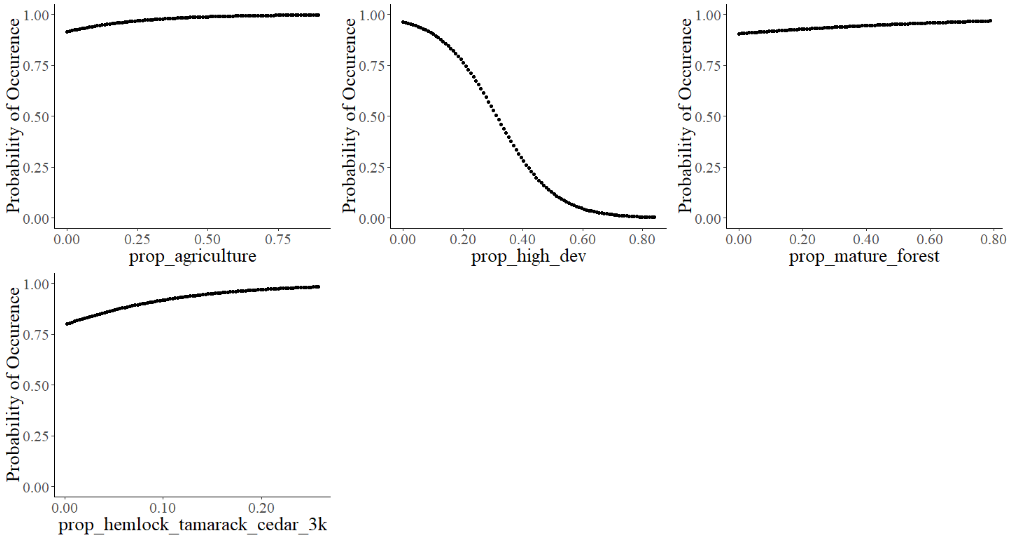
G. Red fox



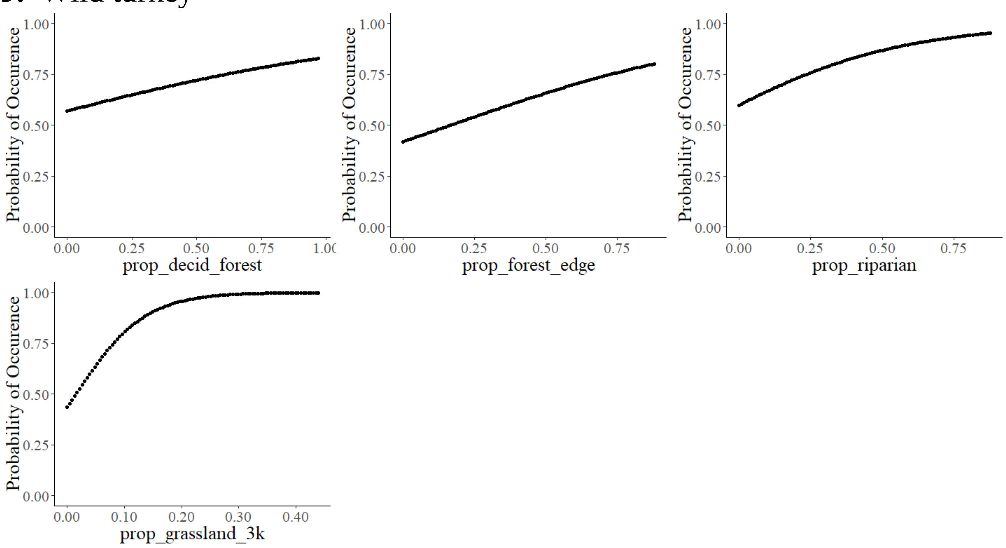
H. Striped skunk



I. White-tailed deer

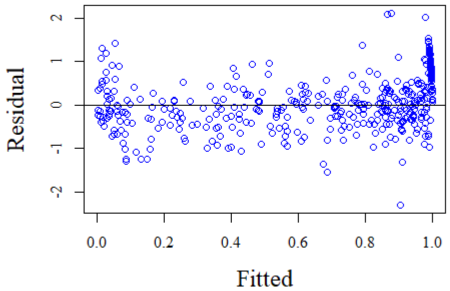


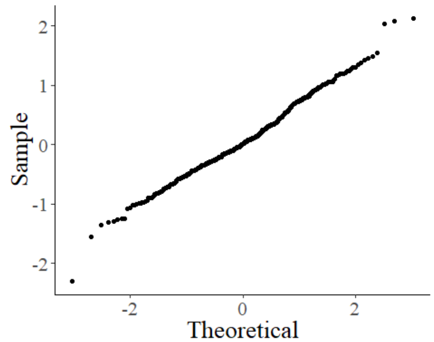
J. Wild turkey



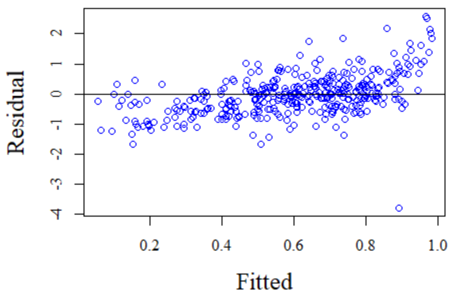
A.4. Diagnostics tests for all focal species (A-J). Model residuals were normally distributed around zero. Model sample and theoretical quantiles display linear relationships, suggesting that both sets of quantiles come from normal distributions.

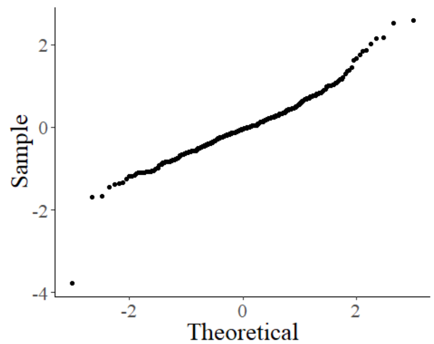
A. American black bear



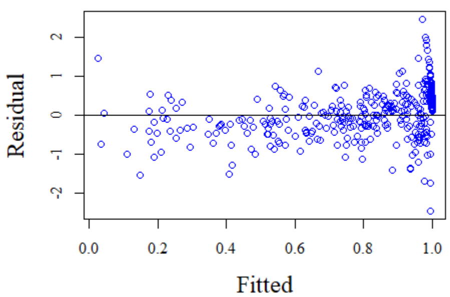


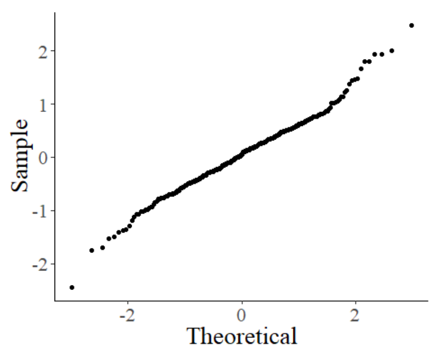
B. Bobcat



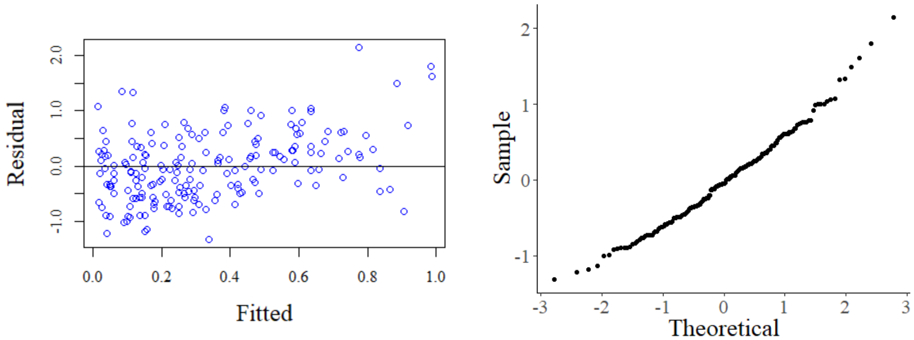


C. Coyote

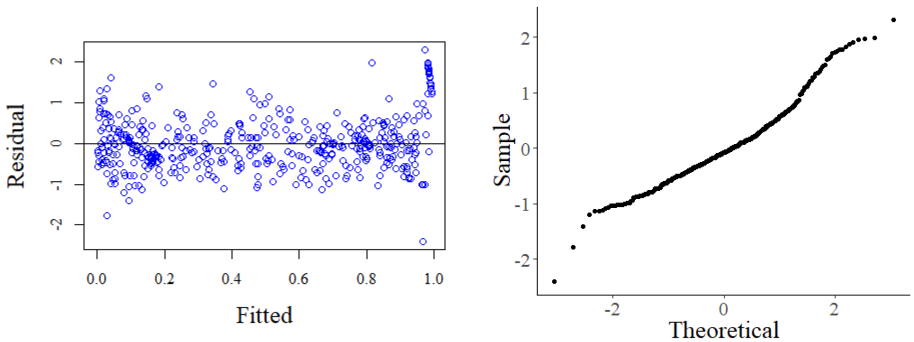




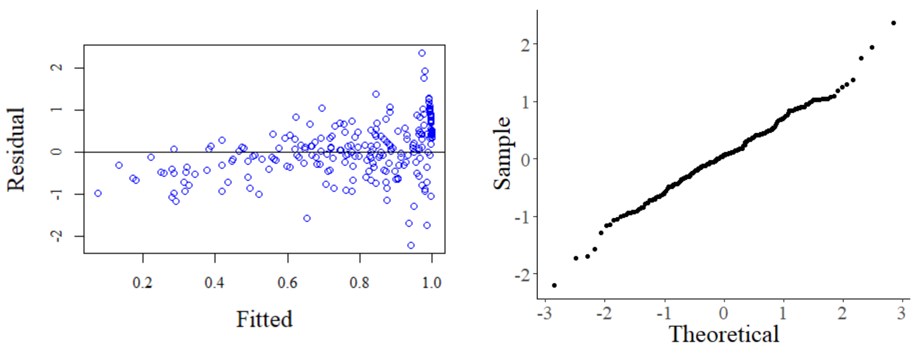
D. Gray fox



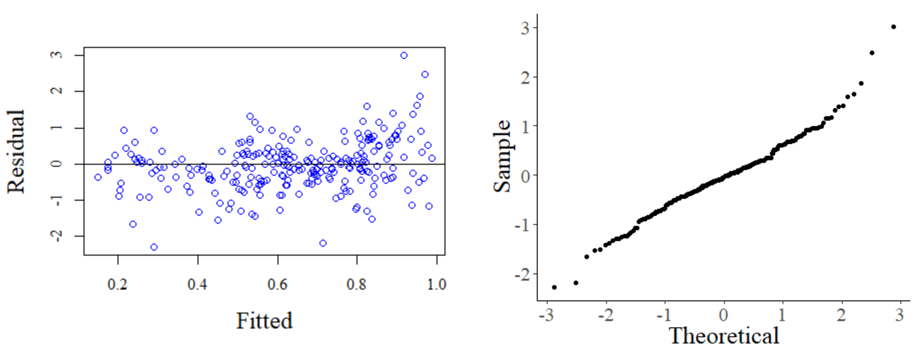
E. Moose



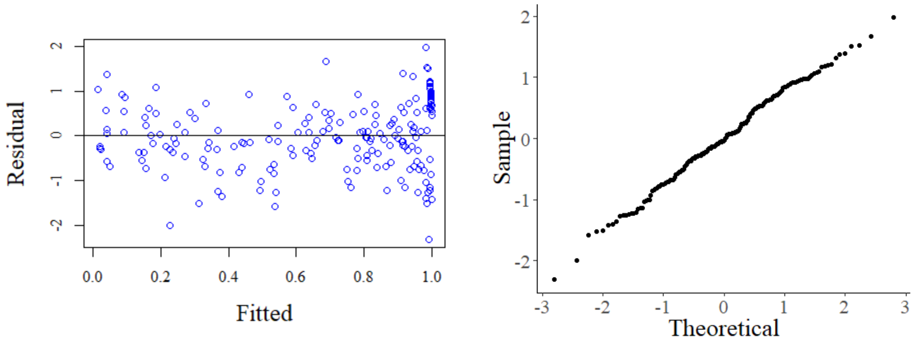
F. Raccoon



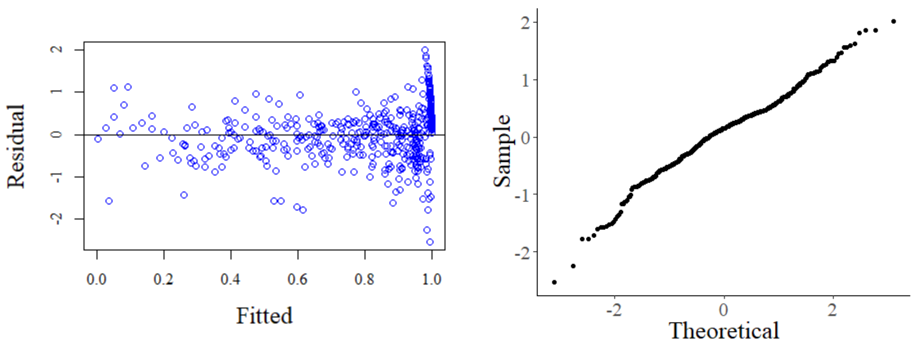
G. Red fox



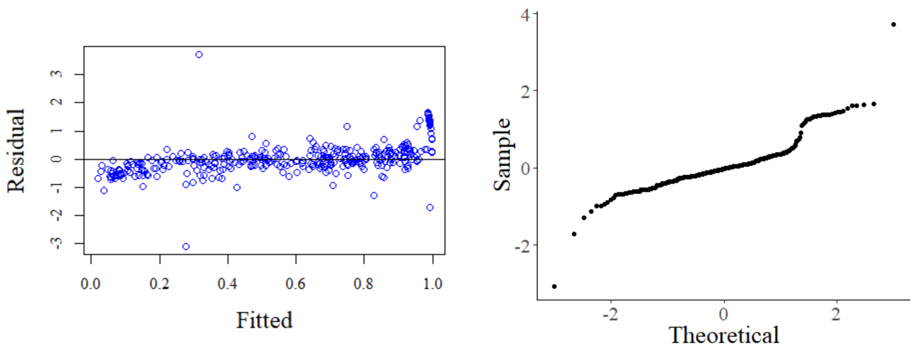
H. Striped skunk



I. White-tailed deer



J. Wild turkey



APPENDIX B

B.1. Pre-survey questionnaire with questions followed by possible responses.

Questions:

1. Gender
    a. Female
    b. Male
    c. Prefer Not to Answer

2. Age
    a. <25
    b. 25-34
    c. 35-44
    d. 45-54
    e. 55-64
    f. 65+
    g. Prefer Not to Answer

3. Which of these best describes your role as an expert? (select all that apply)
    a. Scientist
    b. Manager
    c. Forester
    d. Hunter
    e. Trapper
    f. Agency personnel
    g. NGO personnel
    h. Consultant
    i. Community member
    j. Other

4. Does your expertise derive primarily from literature or field work?
    a. Entirely from literature
    b. Mostly from literature
    c. 50-50
    d. Mostly from field experience
    e. Entirely from field experience

5. How many years of field experience do you have?
    a. <2 years
    b. 2-4 years
    c. 5-7 years
    d. 8-10 years

   e. >10 years

6. Within the past year, how many months have you spent in the field observing wildlife?
   a. <2 months
   b. 2-4 months
   c. 5-7 months
   d. >8 months

7. Rate your overall confidence in your ability to accurately predict species occupancy (1 = little confidence, 5 = very high confidence).
   a. 1
   b. 2
   c. 3
   d. 4
   e. 5

B.2. Post-survey questionnaire with questions followed by possible responses.

Questions:

1. Estimate the amount of time you spent on this survey.
    a. <2 hours
    b. 2-4 hours
    c. 4-6 hours
    d. 6-8 hours
    e. 8+ hours

2. How much time was spent actively evaluating sites?
    a. <1 hour
    b. 1-1.5 hours
    c. 1.5-2 hours
    d. 2-2.5 hours
    e. 2.5-3 hours
    f. 3-3.5 hours
    g. 3.5-4 hours, 4+ hours

3. How many sites could you evaluate in one sitting before feeling fatigued/inconsistent?
    a. <5
    b. 5-10
    c. 10-15
    d. 15-20
    e. 20-25
    f. 25-30
    g. >30

4. How many sites could you evaluate overall before feeling fatigued/inconsistent?
    a. <10
    b. 10-20
    c. 20-30
    d. Could have done up to 50
    e. Could have done >50

5. Rate the utility of the embedded map on a scale of 1 (unhelpful) to 5 (essential).
    a. 1
    b. 2
    c. 3
    d. 4
    e. 5

6. Rate the utility of the pie charts on a scale of 1 (unhelpful) to 5 (essential).
    a. 1
    b. 2
    c. 3
    d. 4
    e. 5

7. Rate the utility of the variable information listed beneath the Google map on a scale of 1 (unhelpful) to 5 (essential).
    a. 1
    b. 2
    c. 3
    d. 4
    e. 5

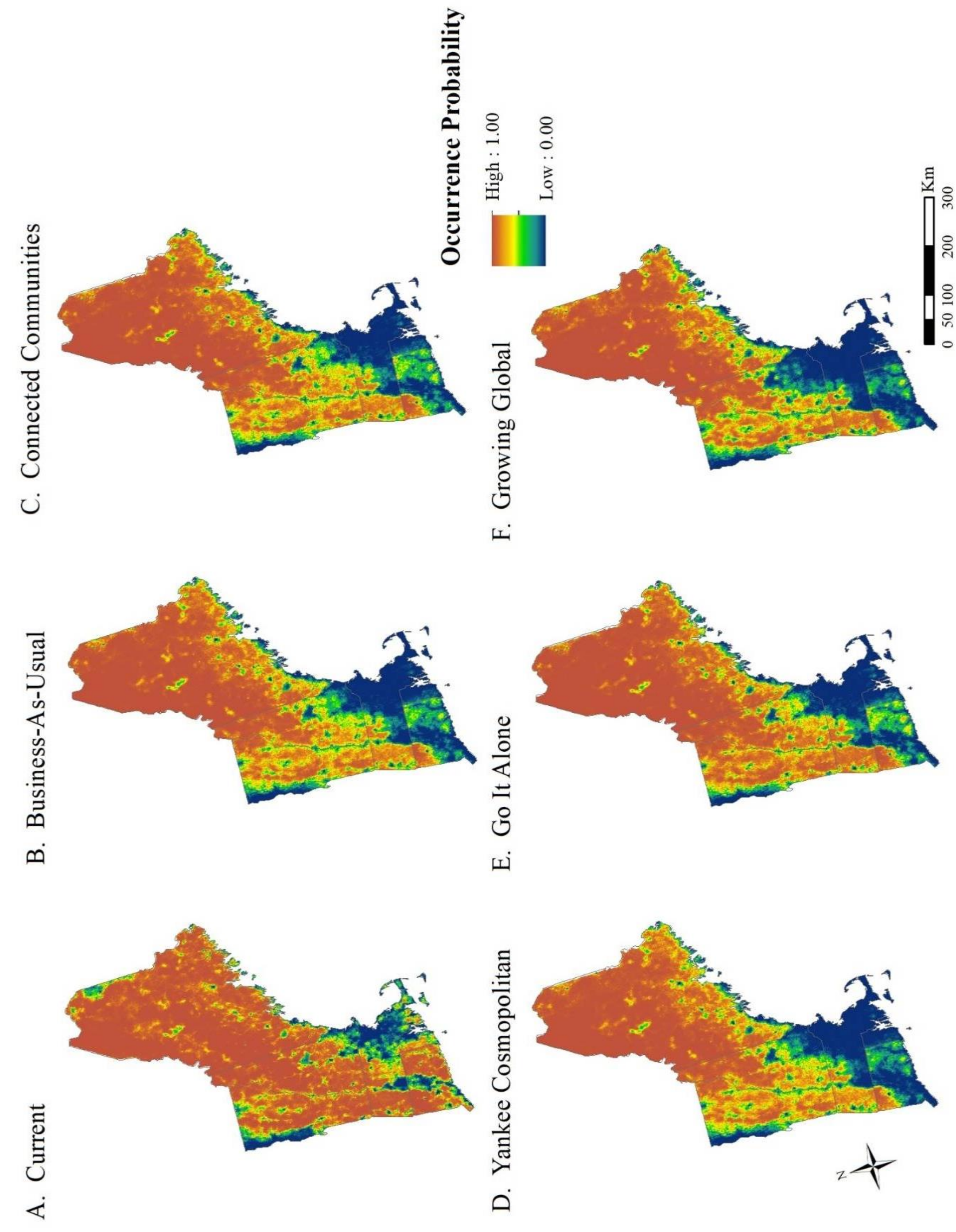
8. Was site-level habitat information more/less influential to your estimate than the geographic location of the site (i.e., the Google map)?
    a. Only considered habitat information
    b. Mostly considered habitat information
    c. 50-50
    d. Mostly considered geographic location
    e. Only considered geographic location

9. Do you have any additional comments or suggestions for future expert elicitation research?

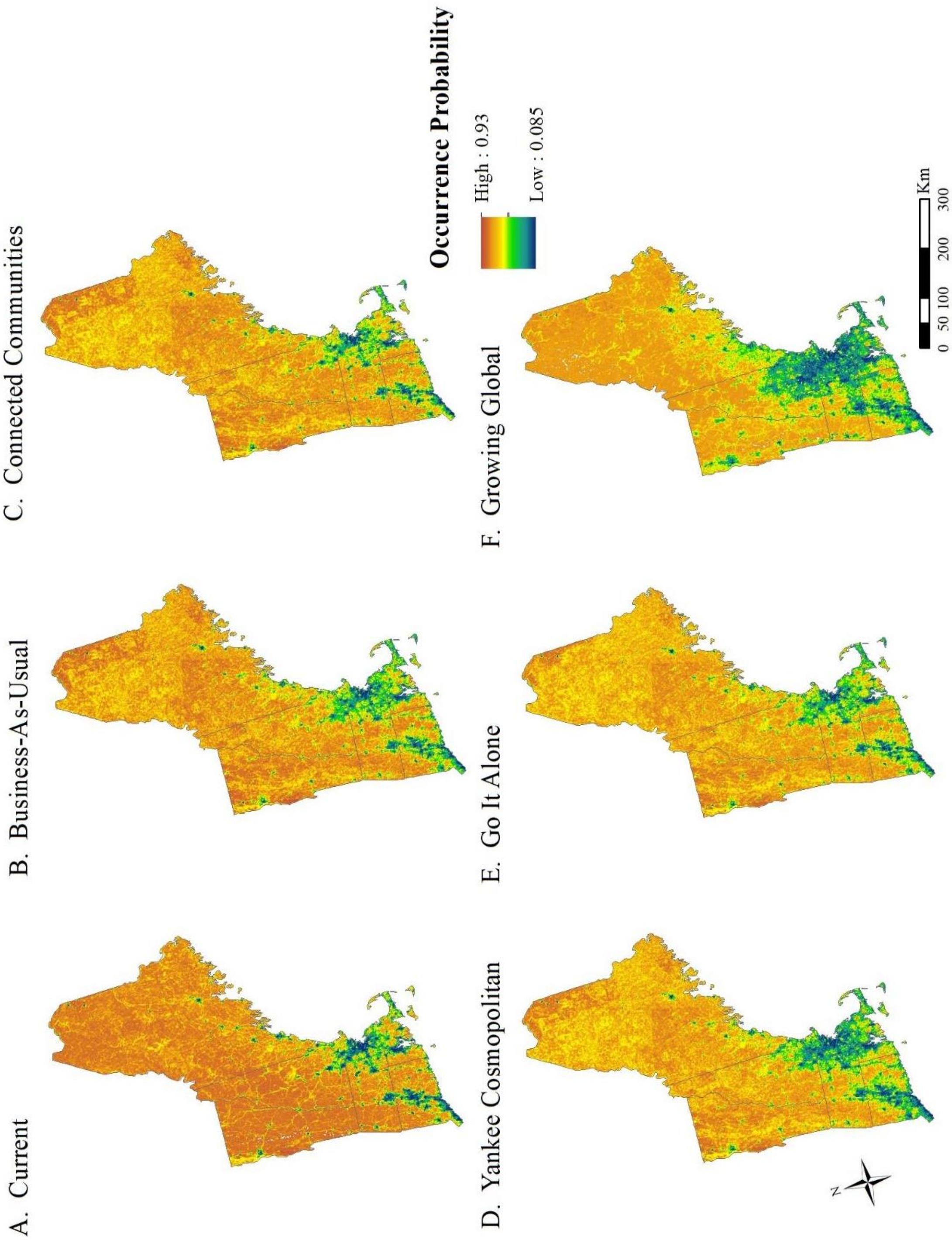
APPENDIX C

C.1. Scenario-simulated distributions of 10 wildlife species throughout New England as projected by current (2010) conditions and each of the NELFP scenarios: (B) Business-As-Usual, (C) Connected Communities, (D) Yankee Cosmopolitan, (E) Go It Alone, and (F) Growing Global. Distribution was projected as occurrence probabilities derived from species distribution models developed through expert elicitation and mixed modeling methods (see Pearman-Gillman et al., 2020).

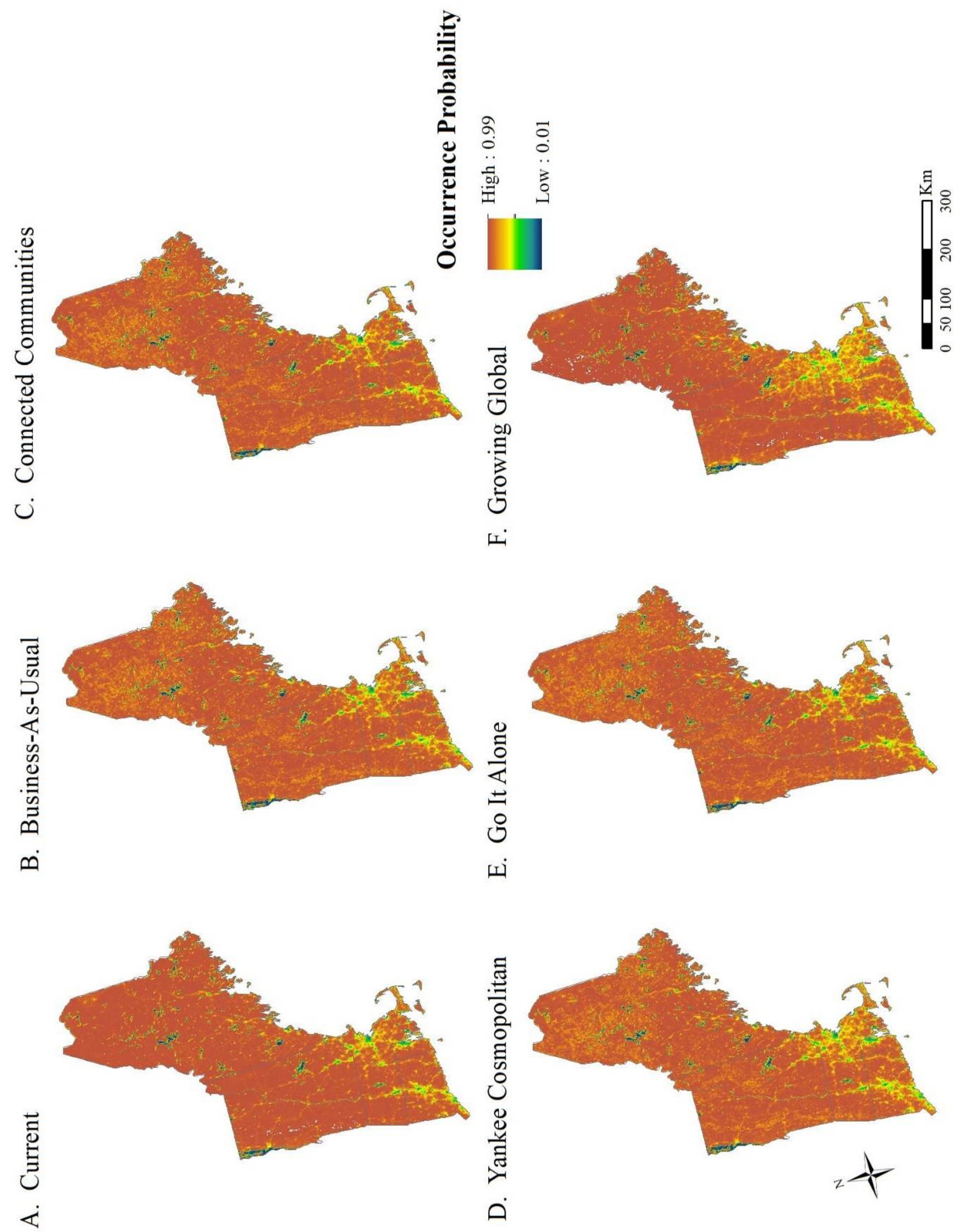
American black bear



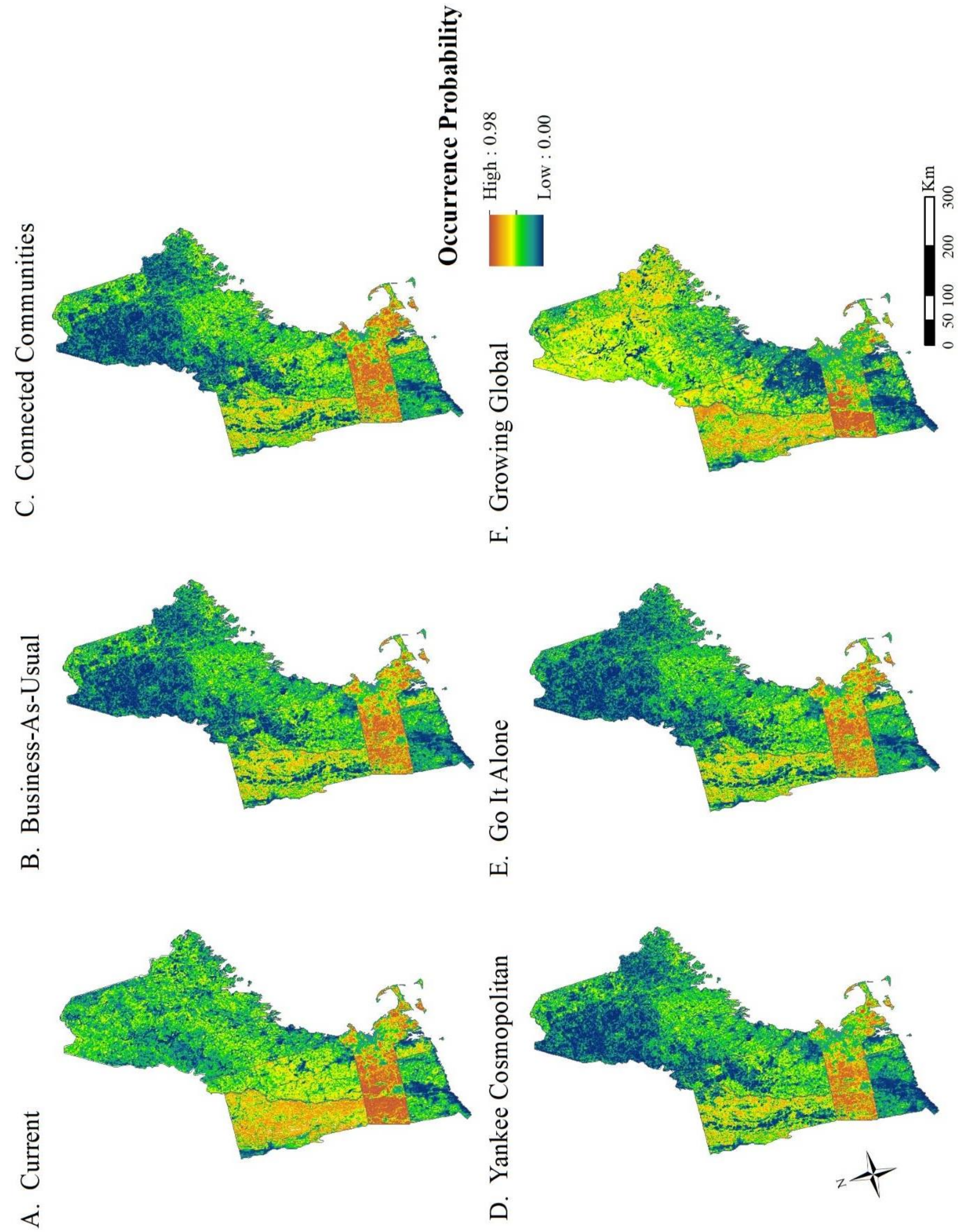
Bobcat


A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 0.93
Low : 0.085
0 50 100 200 300
Km
N

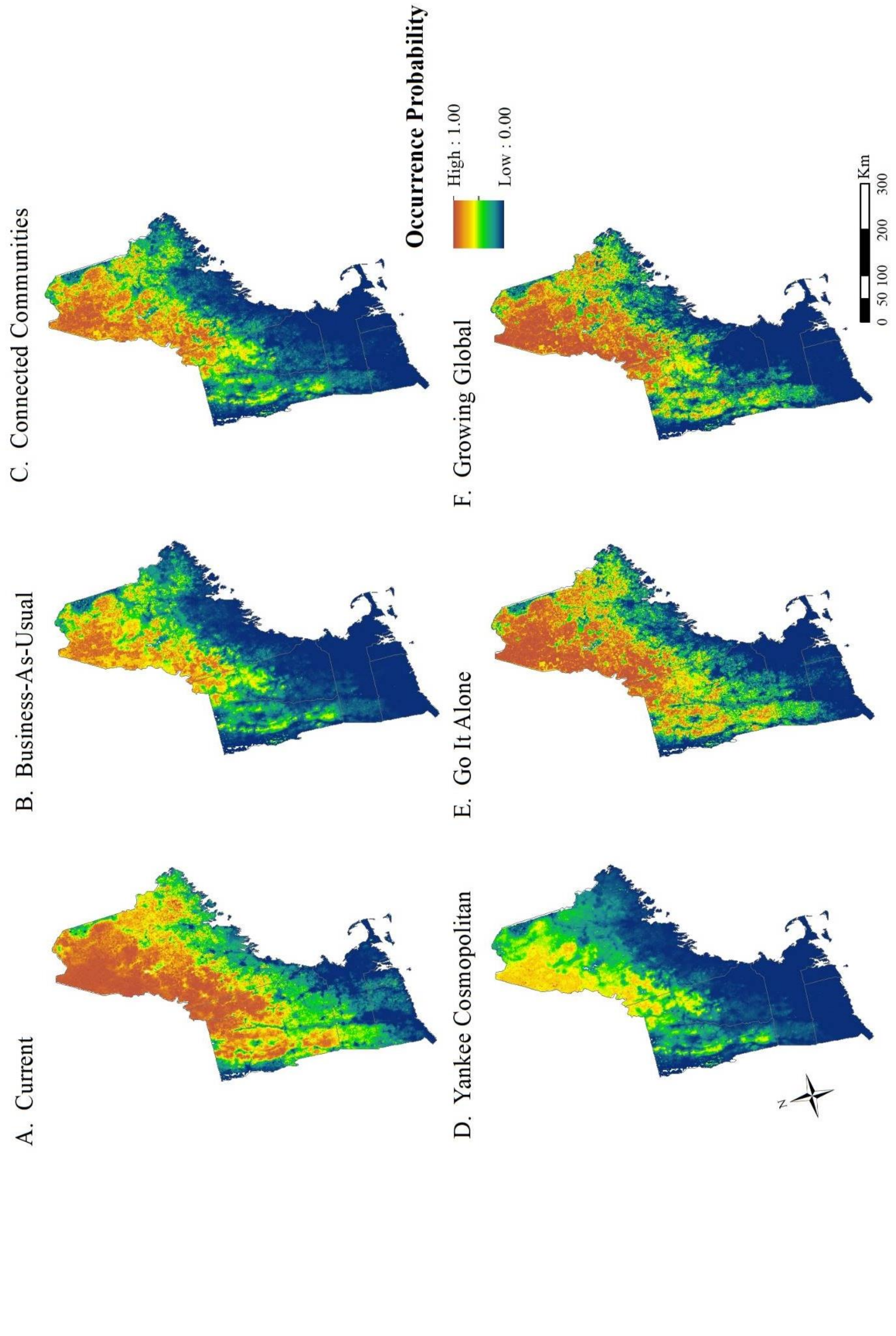
Coyote


A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 0.99
Low : 0.01
Km
0 50 100 200 300
N

Gray fox

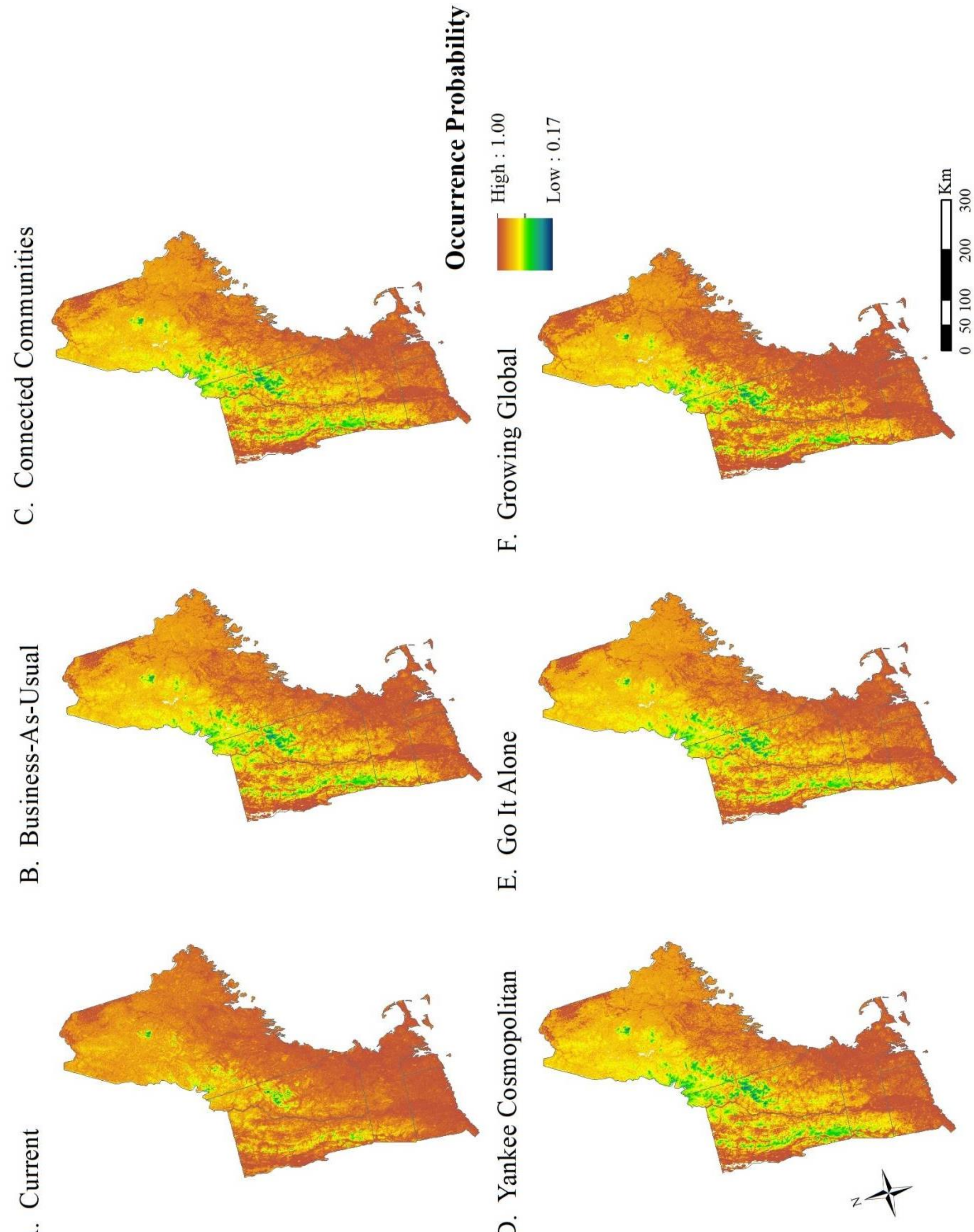

A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 0.98
Low : 0.00
0 50 100 200 300
Km
N

Moose

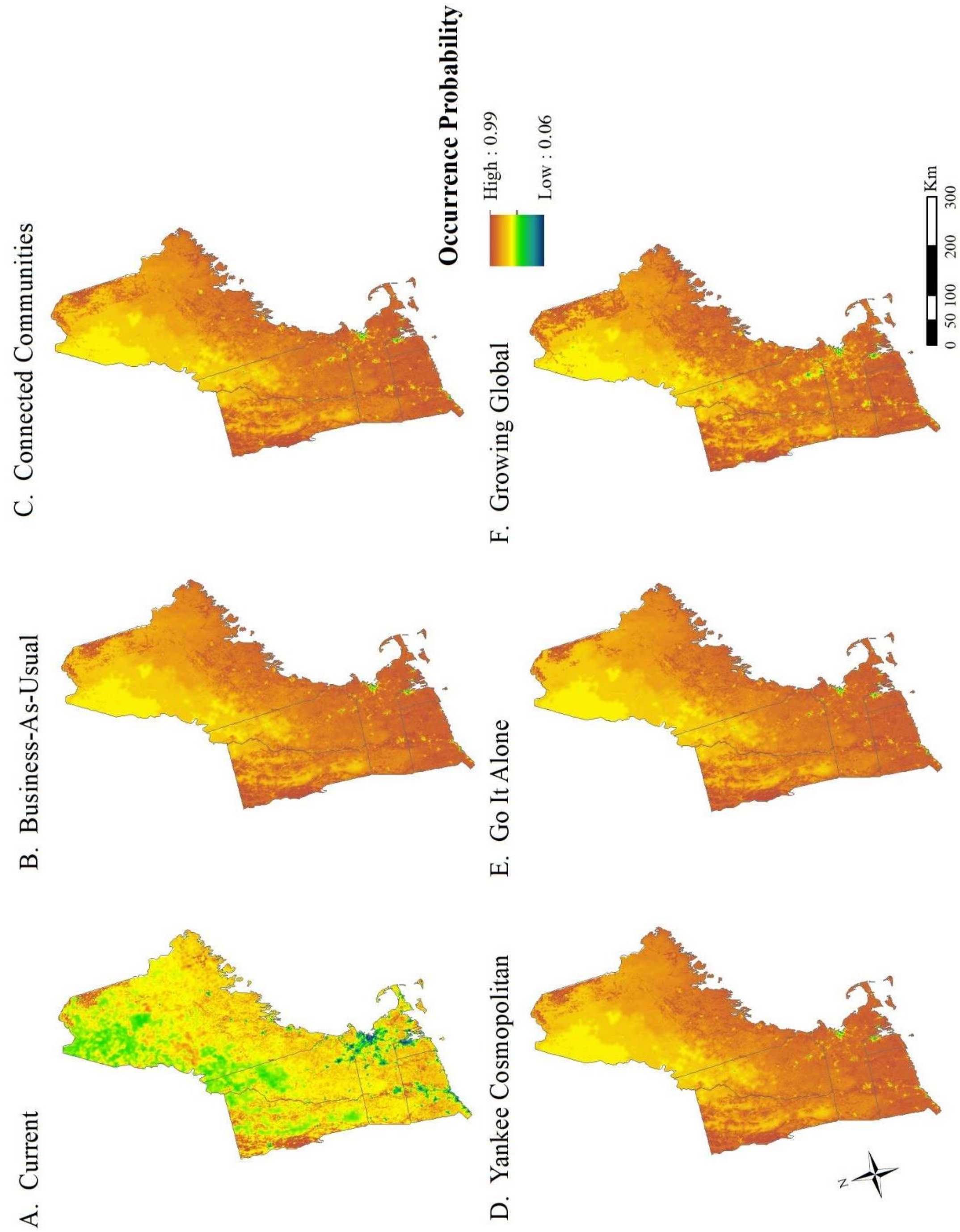


A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 1.00
Low : 0.00
0 50 100 200 300
Km
N

Raccoon

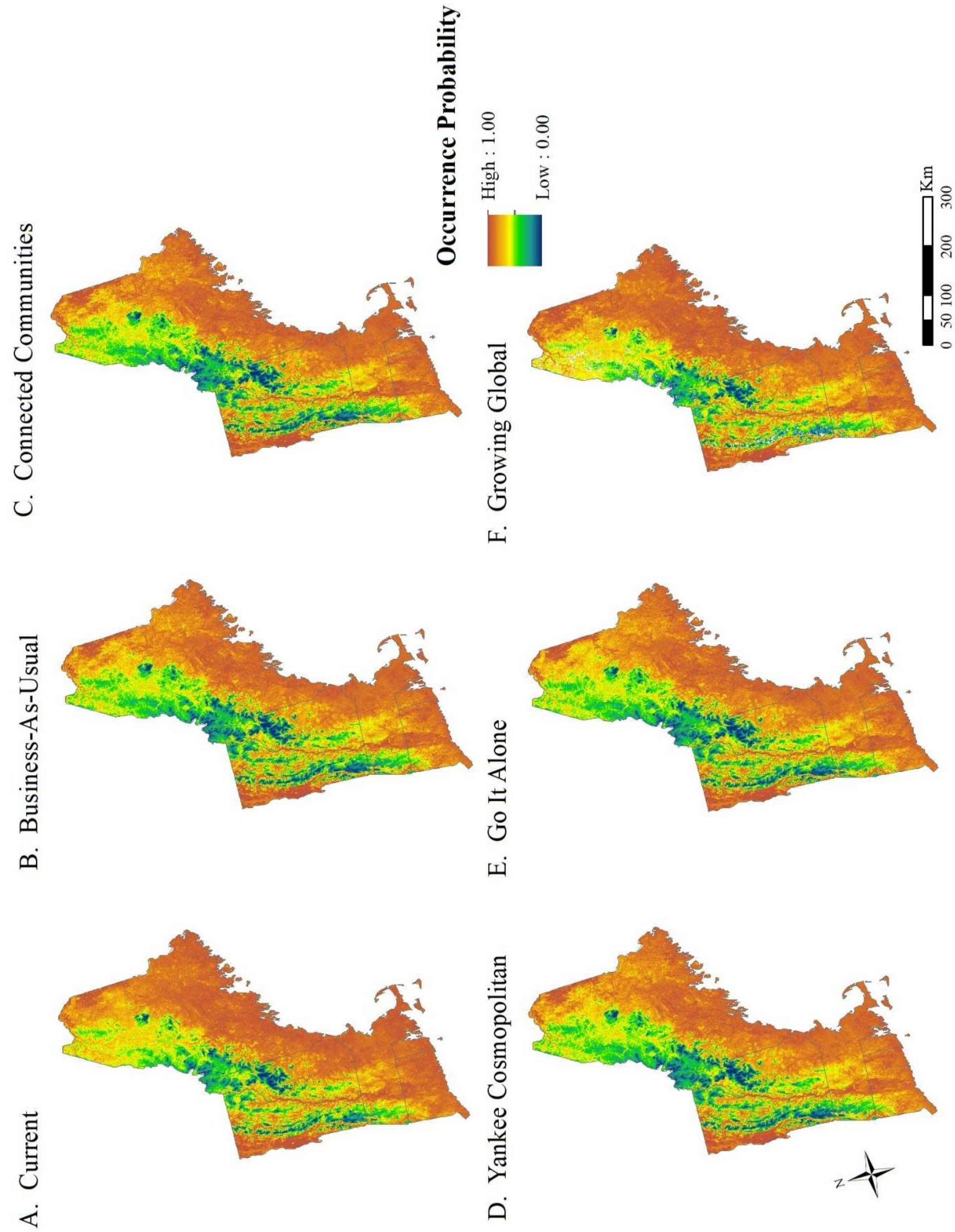

A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 1.00
Low : 0.17
0 50 100 200 300
Km
N

Red fox

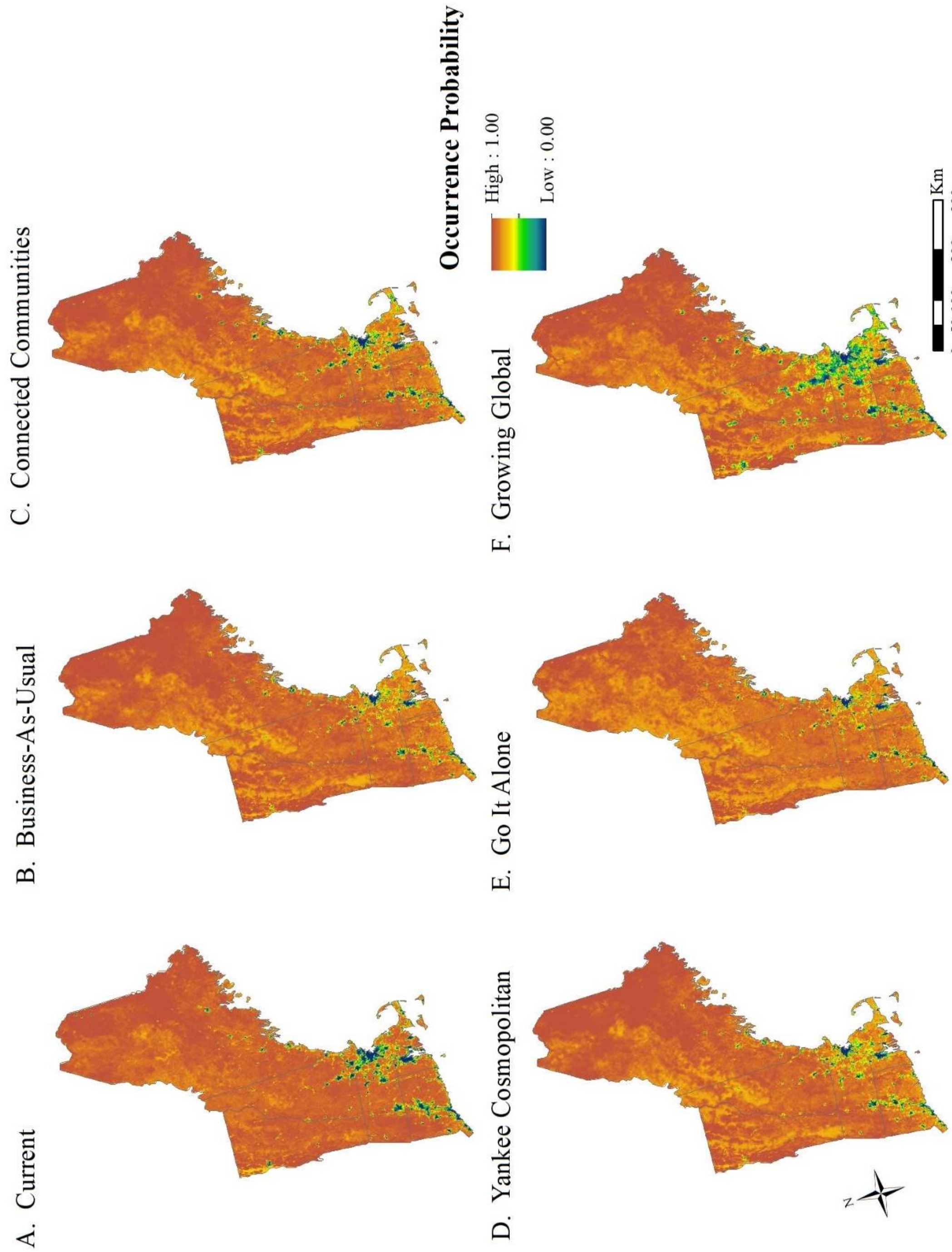


A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 0.99
Low : 0.06
0 50 100 200 300
Km
N

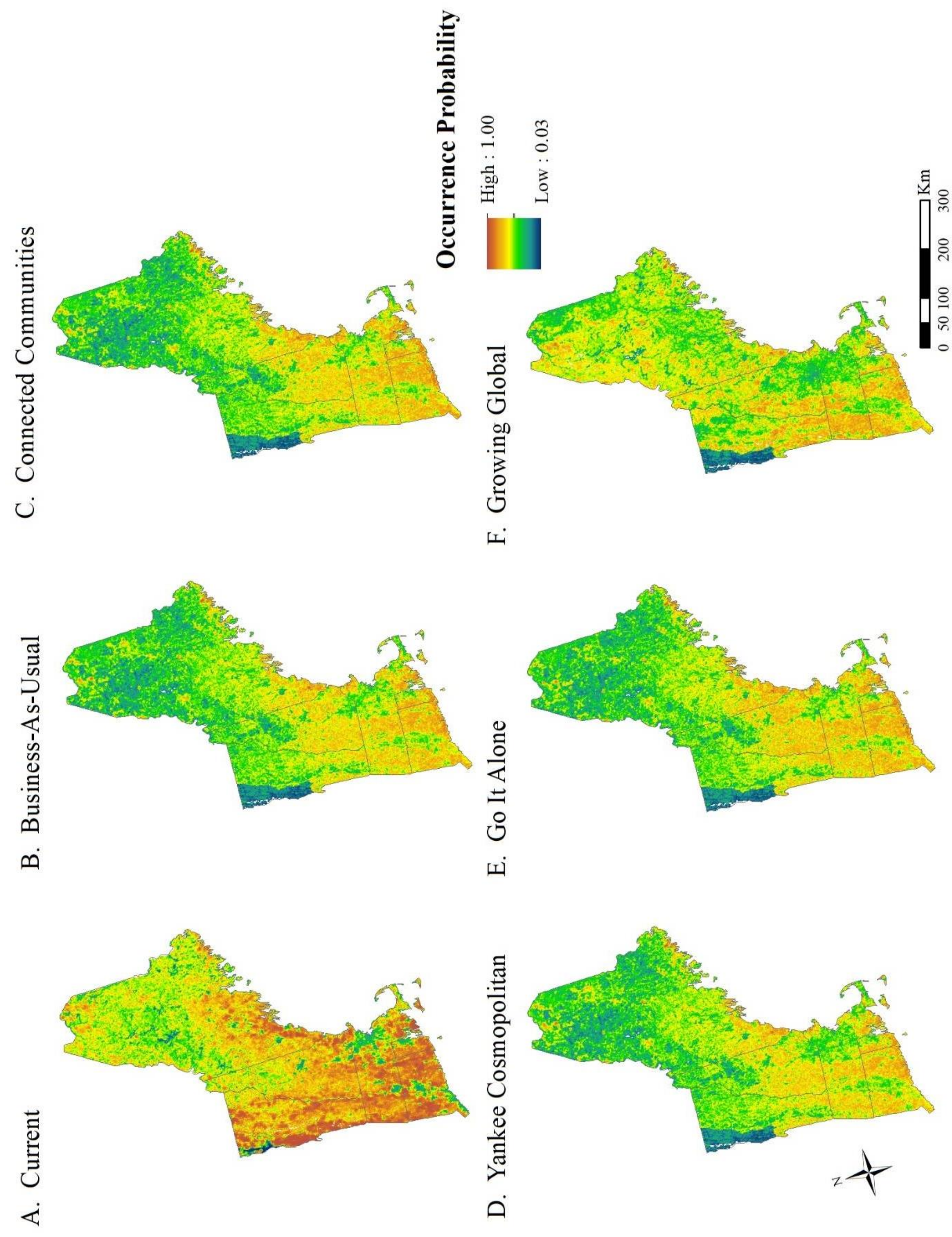
Striped skunk



White-tailed deer



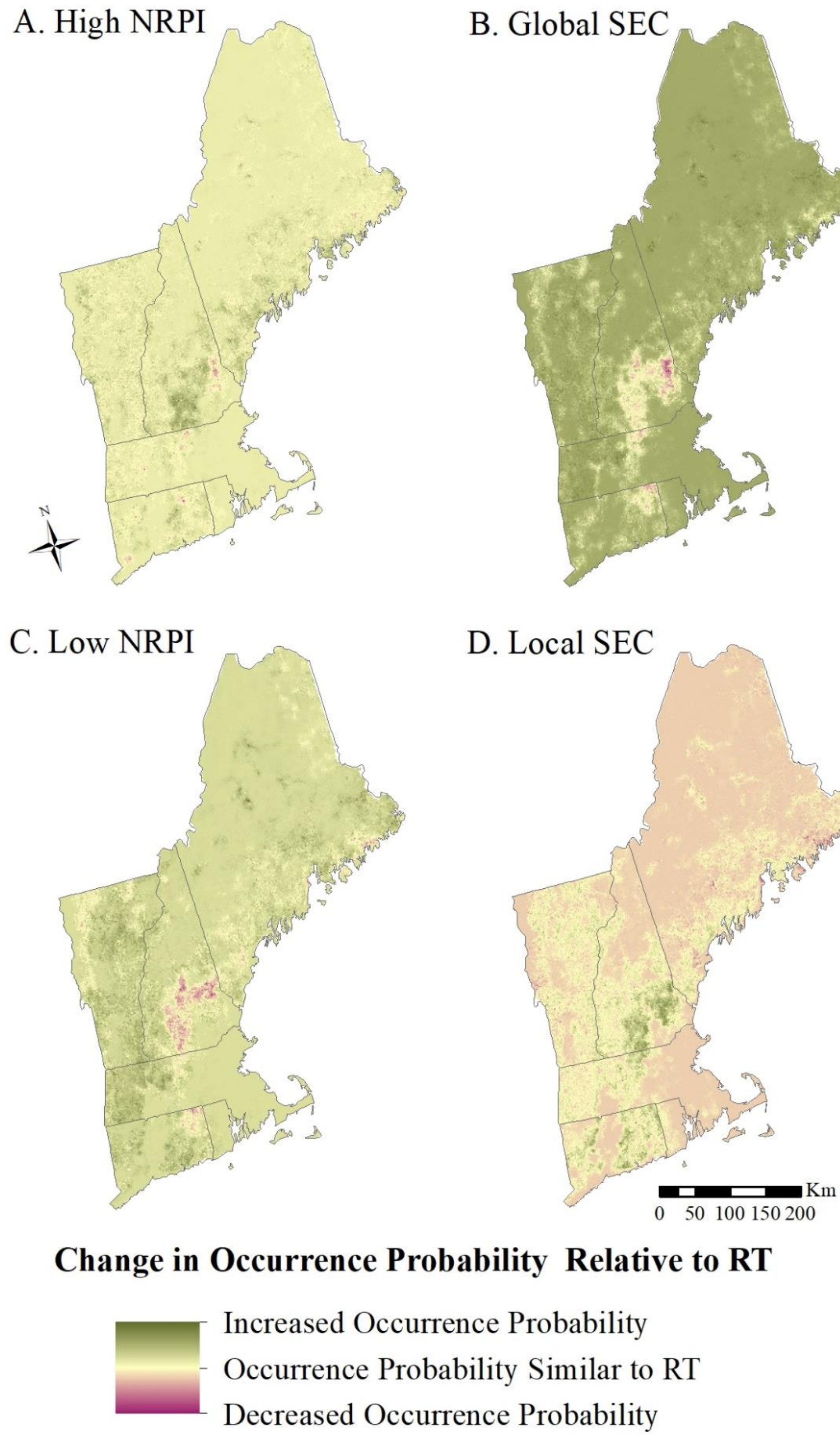
Wild turkey



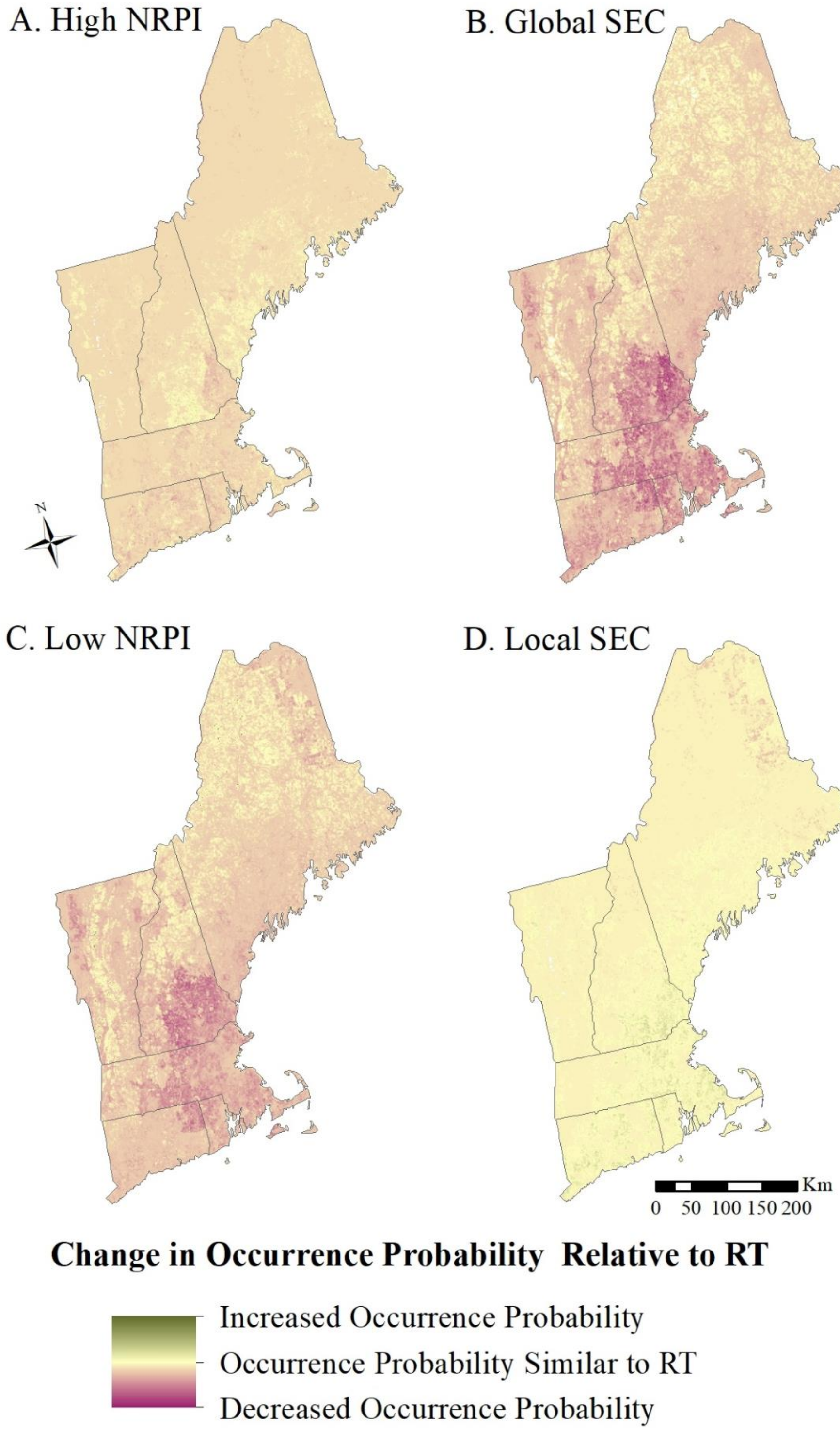
A. Current
B. Business-As-Usual
C. Connected Communities
D. Yankee Cosmopolitan
E. Go It Alone
F. Growing Global
Occurrence Probability
High : 1.00
Low : 0.03
0 50 100 200 300
Km
N

C.2. Driver isolated distribution change maps for 10 wildlife species identifying areas within the New England region of the northeastern United States where species occurrence was impacted by each isolated driver of landscape change: (A) High natural resource planning and innovation (NRPI), (B) Global socio-economic connectedness (SEC), (C) Low NRPI, and (D) Local SEC. Map values indicate the difference from the recent trends (RT, i.e., Business-As-Usual) baseline and highlight areas where each driver increased or decreased species occurrence likelihood relative to the occurrence likelihood expected under the Business-As-Usual scenario.

American black bear

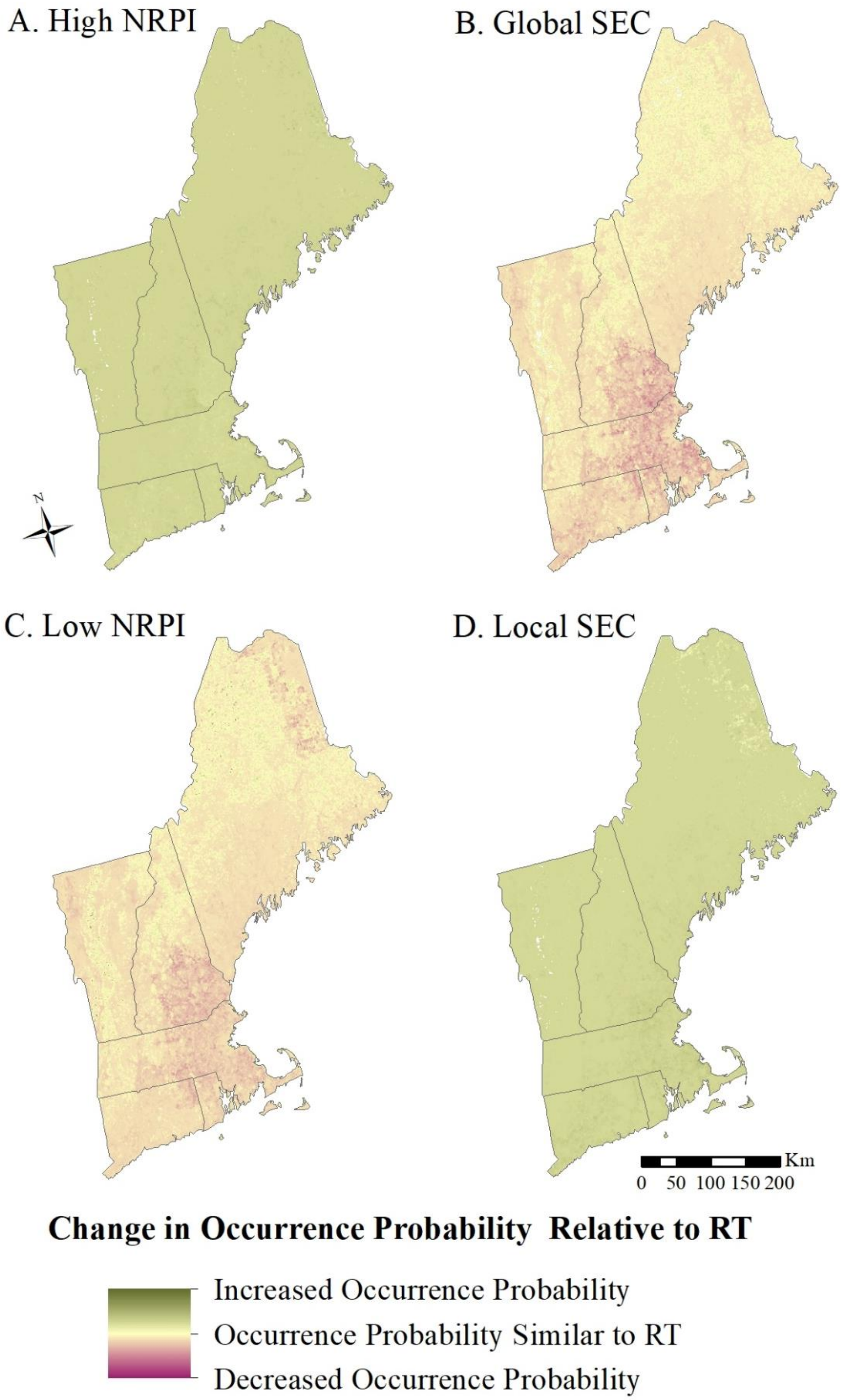


Bobcat

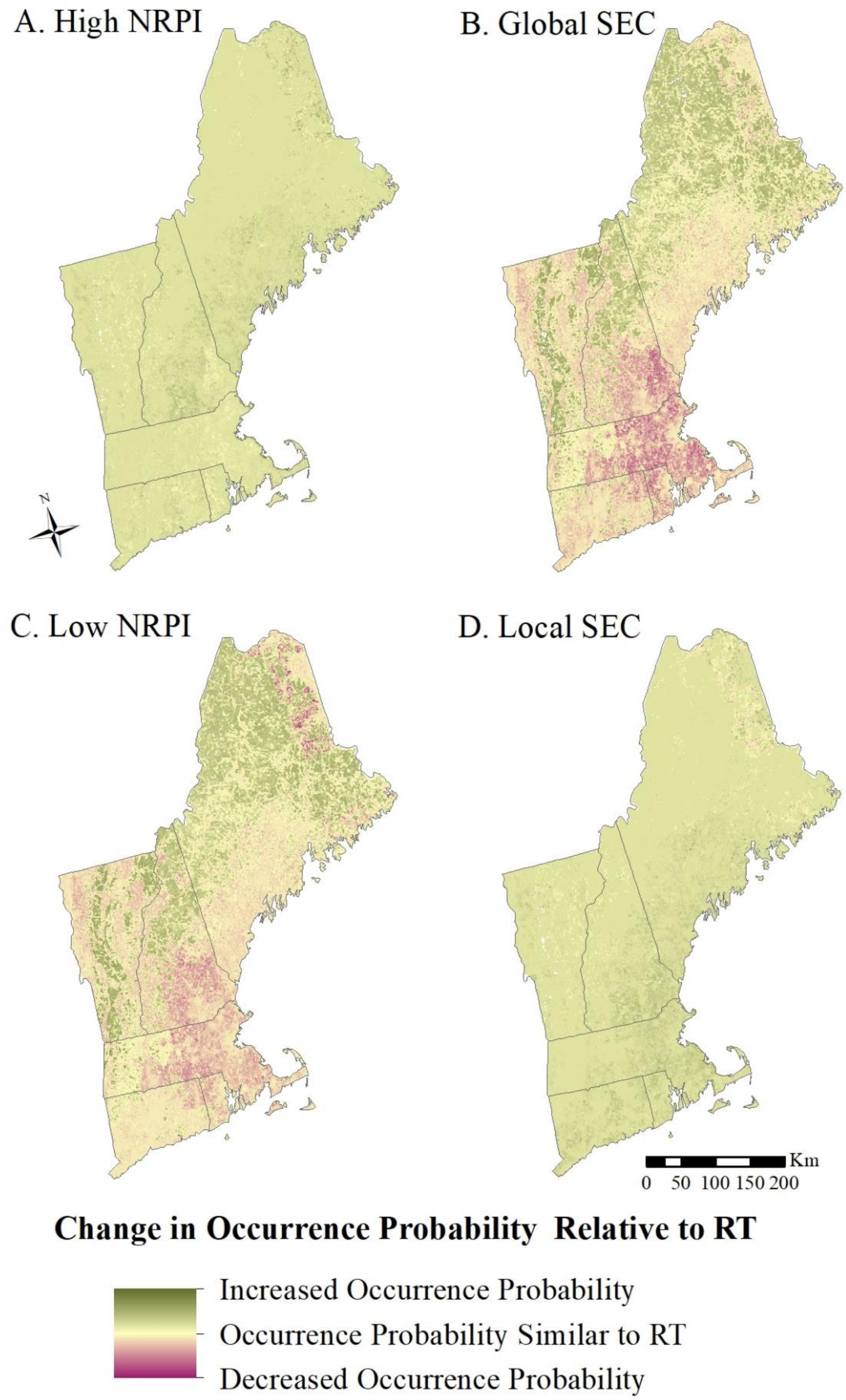


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

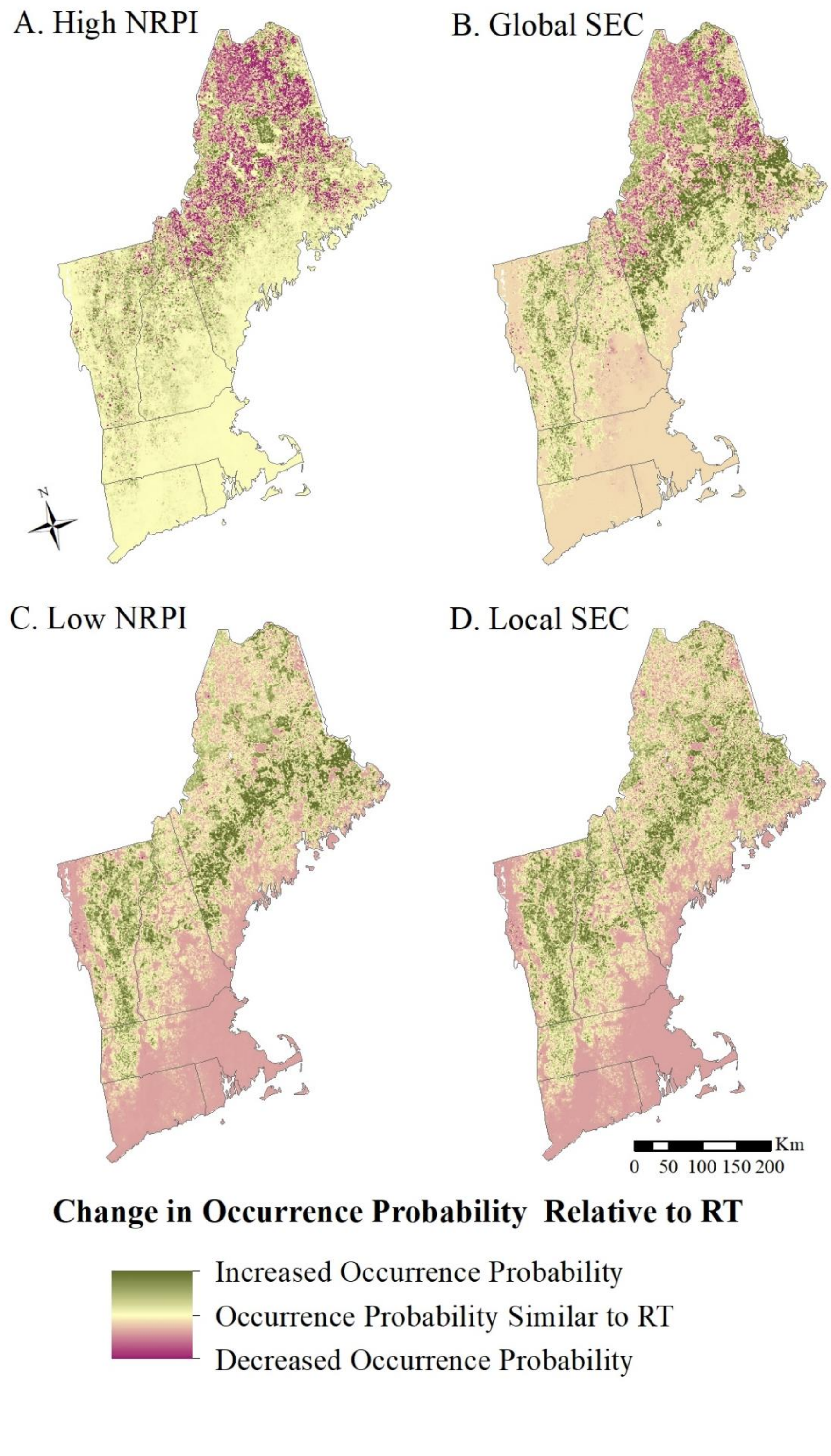
Coyote


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

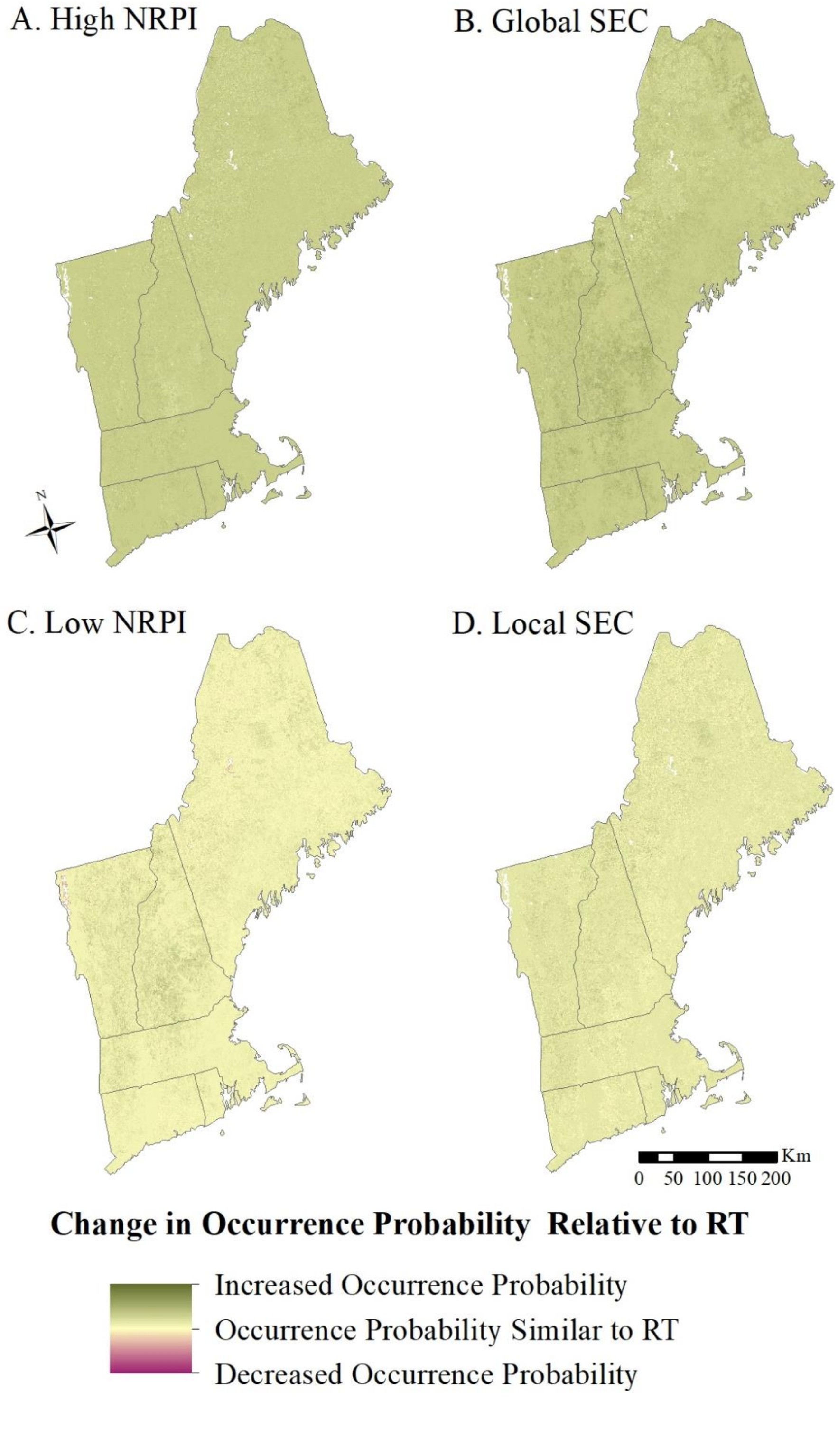
Gray fox


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

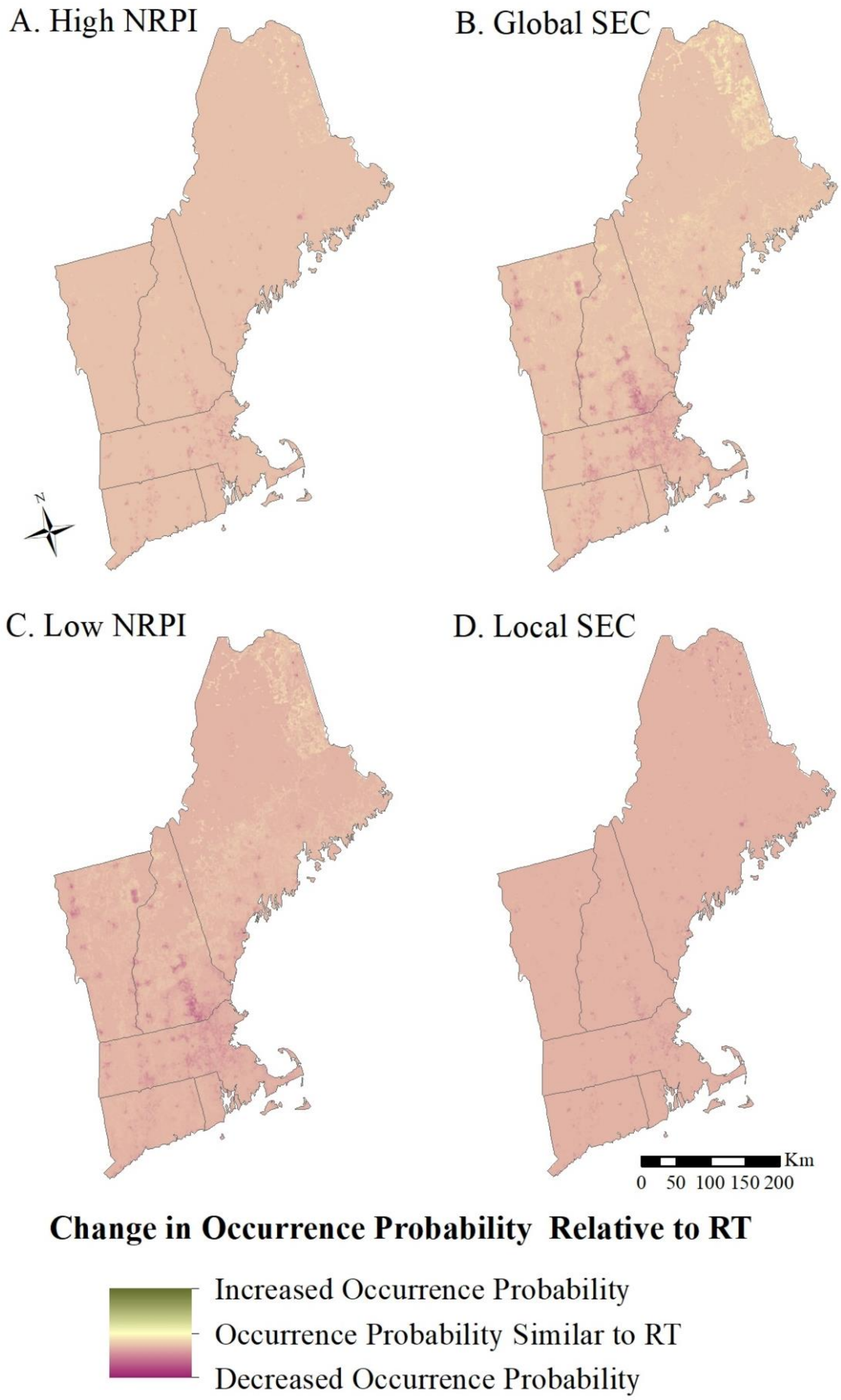
Moose


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

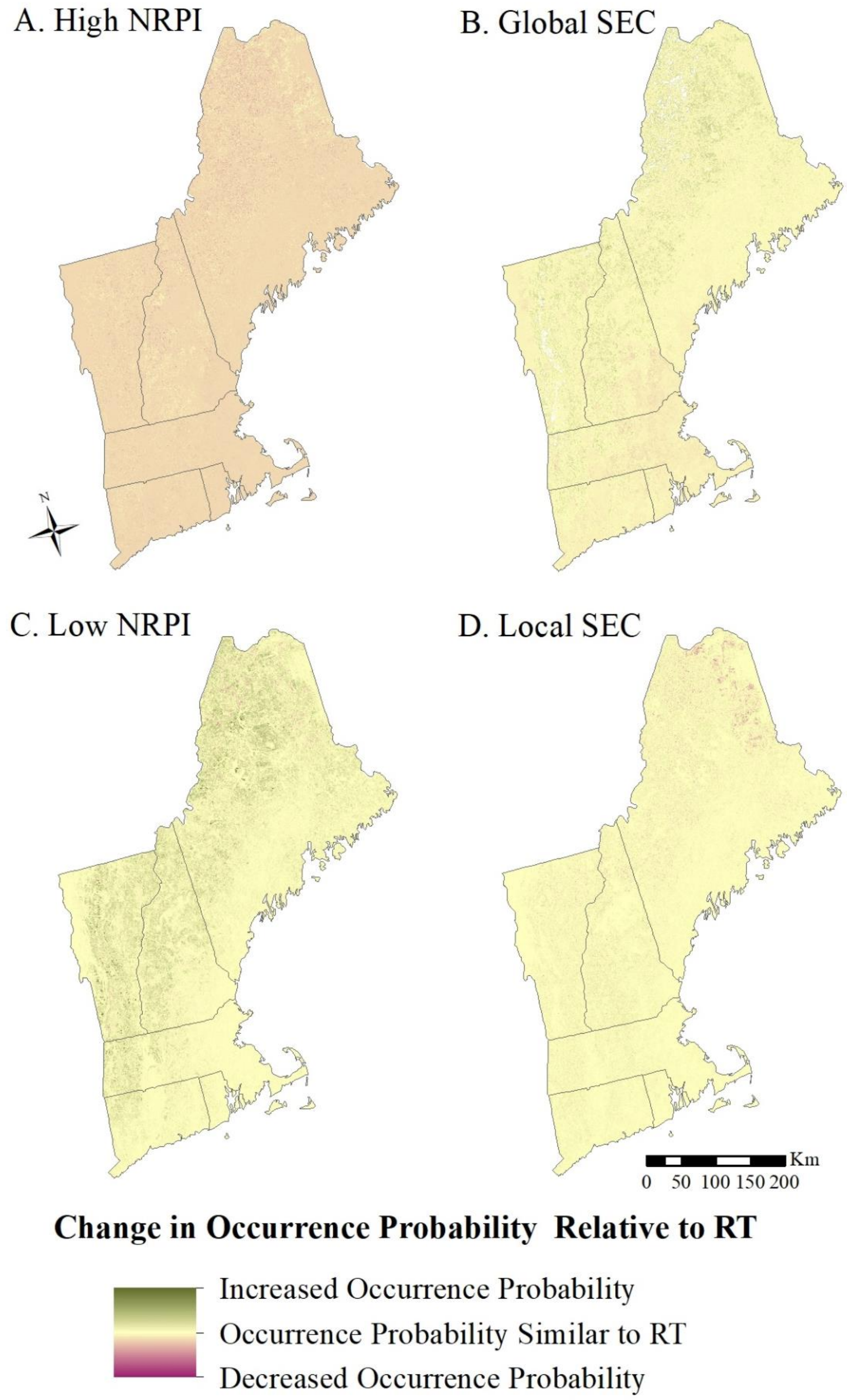
Raccoon


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

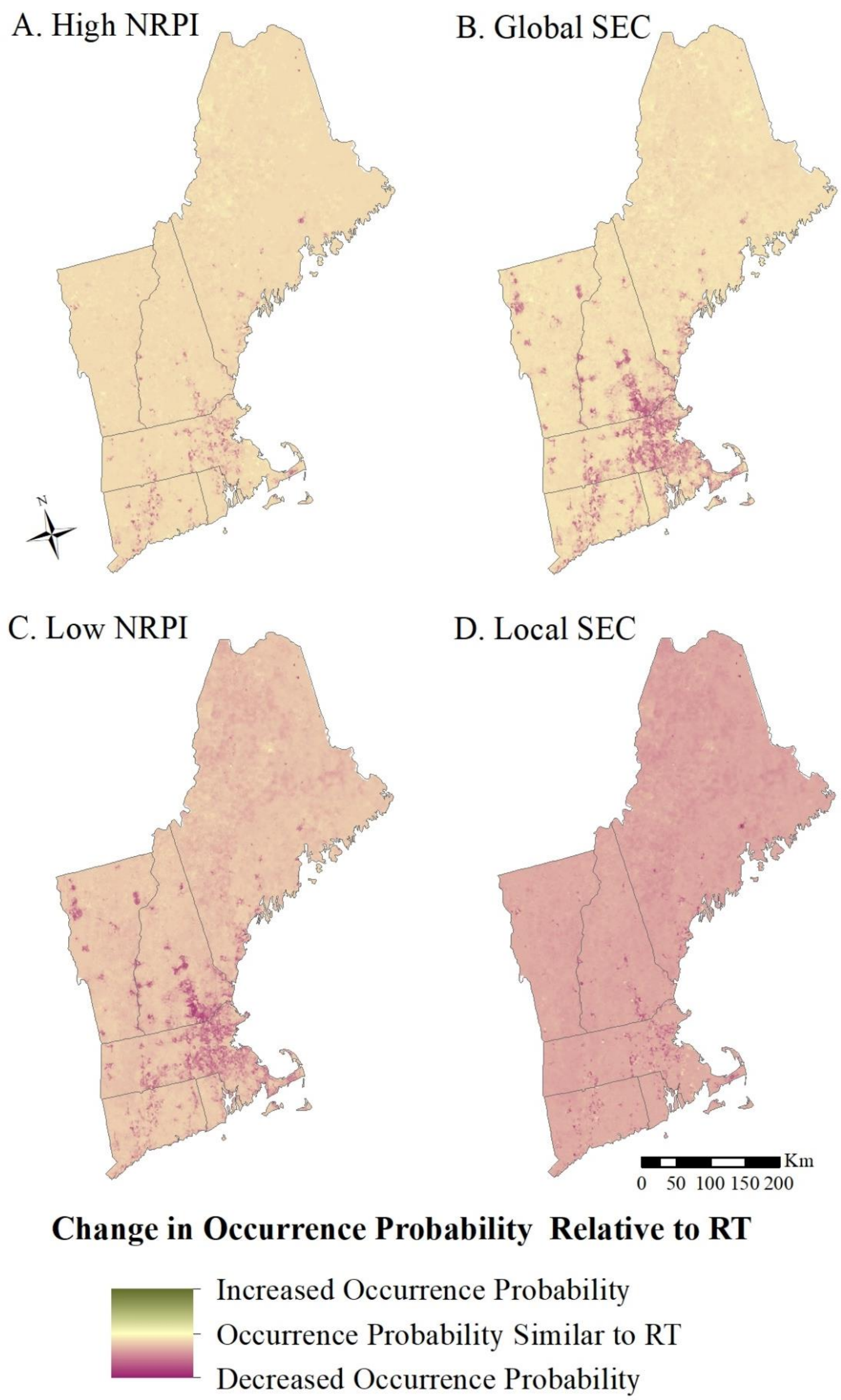
Red fox


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

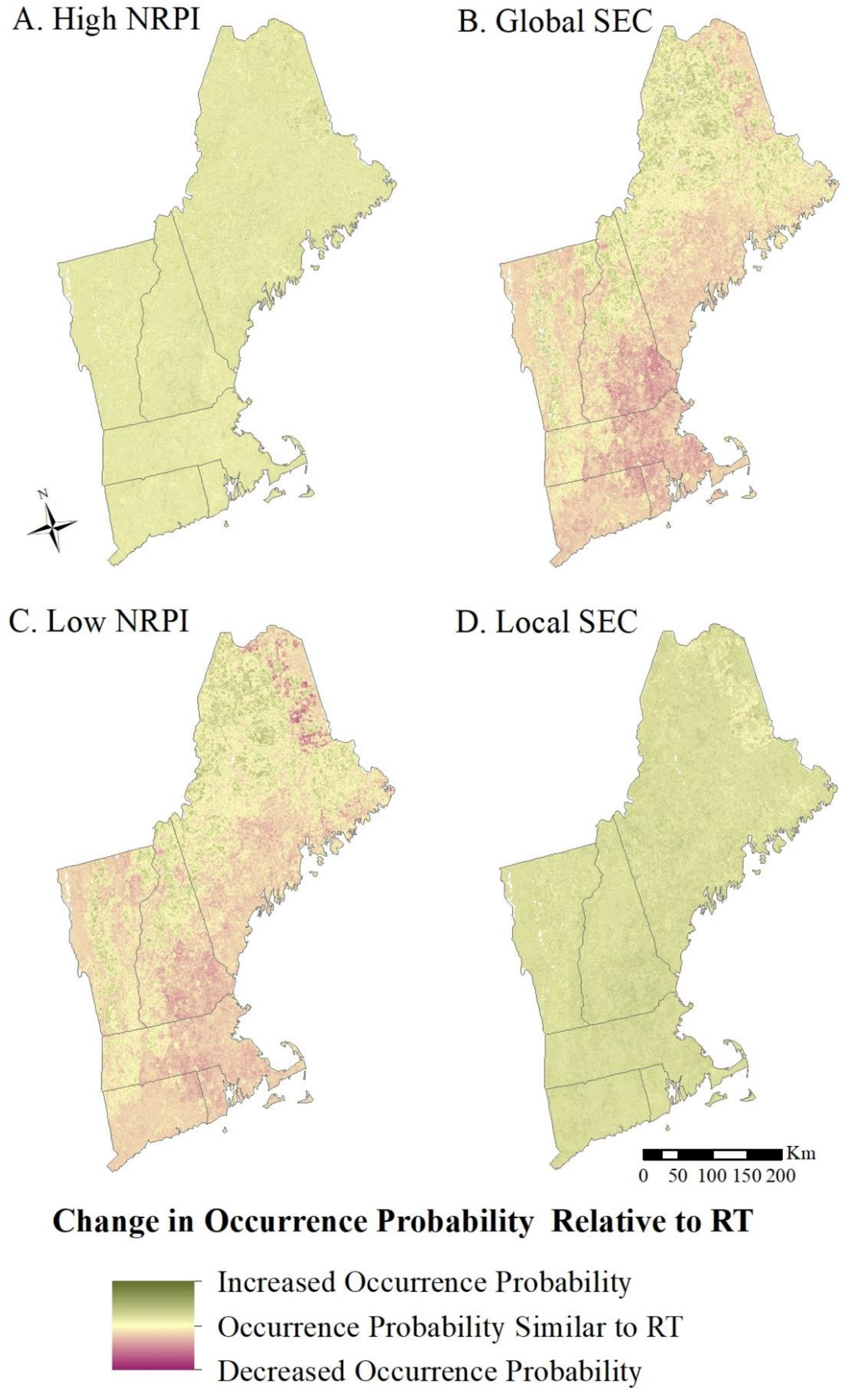
Striped skunk



White-tailed deer



Wild turkey

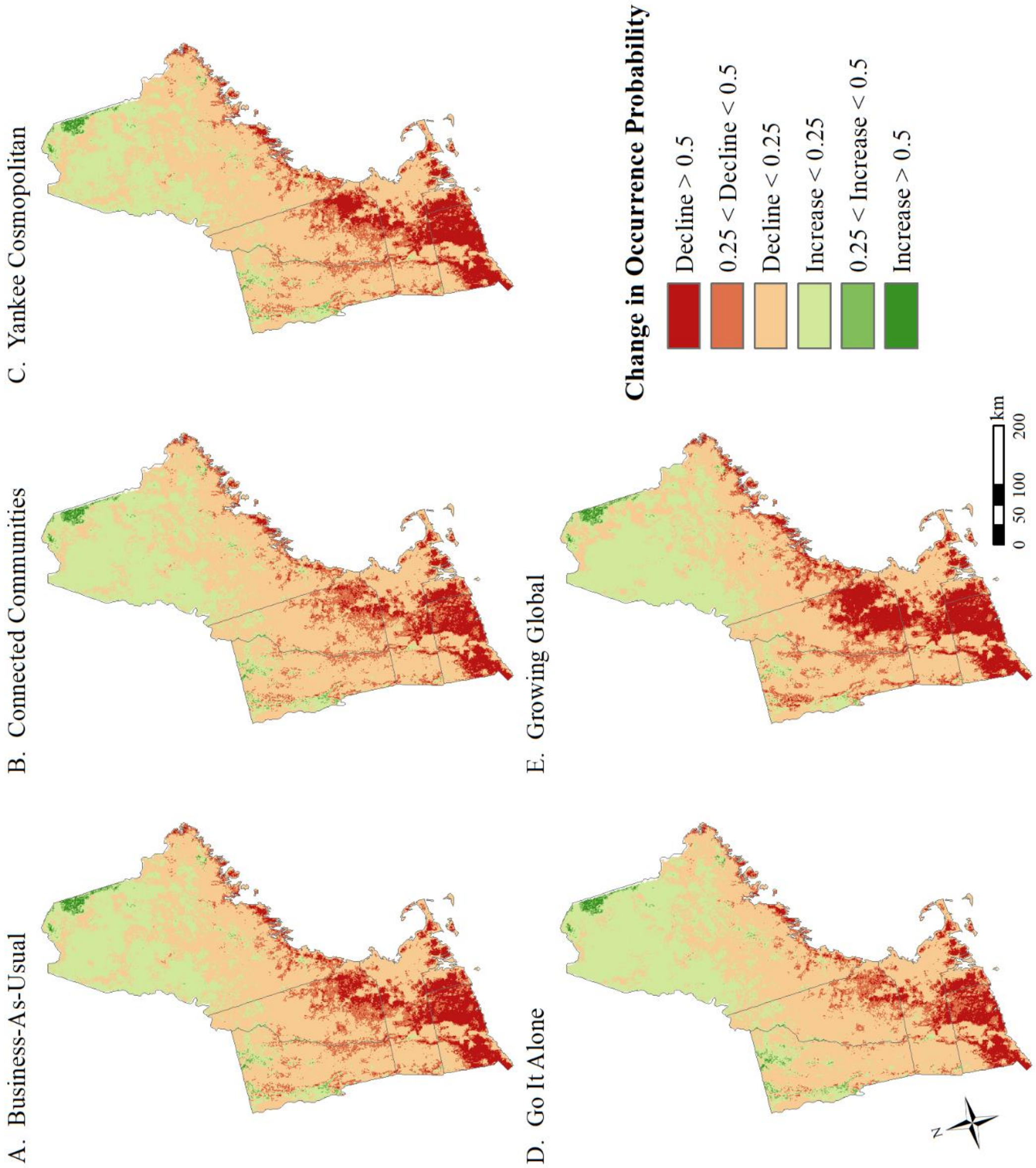


A. High NRPI
B. Global SEC
C. Low NRPI
D. Local SEC
N
Km
0 50 100 150 200
Change in Occurrence Probability Relative to RT
Increased Occurrence Probability
Occurrence Probability Similar to RT
Decreased Occurrence Probability

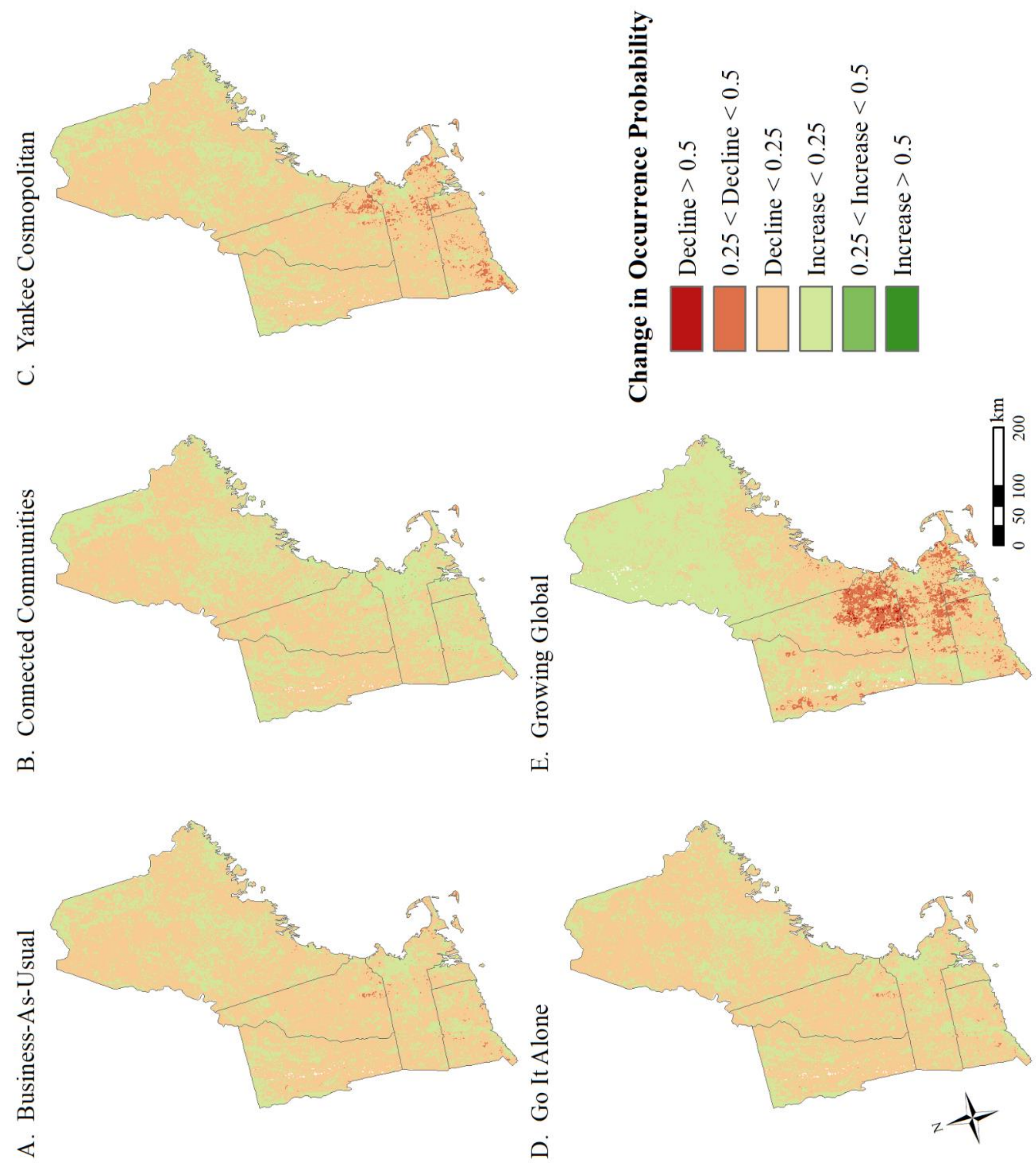
APPENDIX D

D.1. Species scenario-specific distribution change throughout New England, USA.
Distribution change was projected for 10 wildlife species between current (2010) conditions and each of the NELFP scenarios: (A) Business-As-Usual, (B) Connected Communities, (C) Yankee Cosmopolitan, (D) Go It Alone, and (E) Growing Global. Maps display changes in species probability of occurrence, derived from simulated distribution maps for 2010 and 2060 (see Pearman-Gillman et al., 2020 and Pearman-Gillman et al. in review).

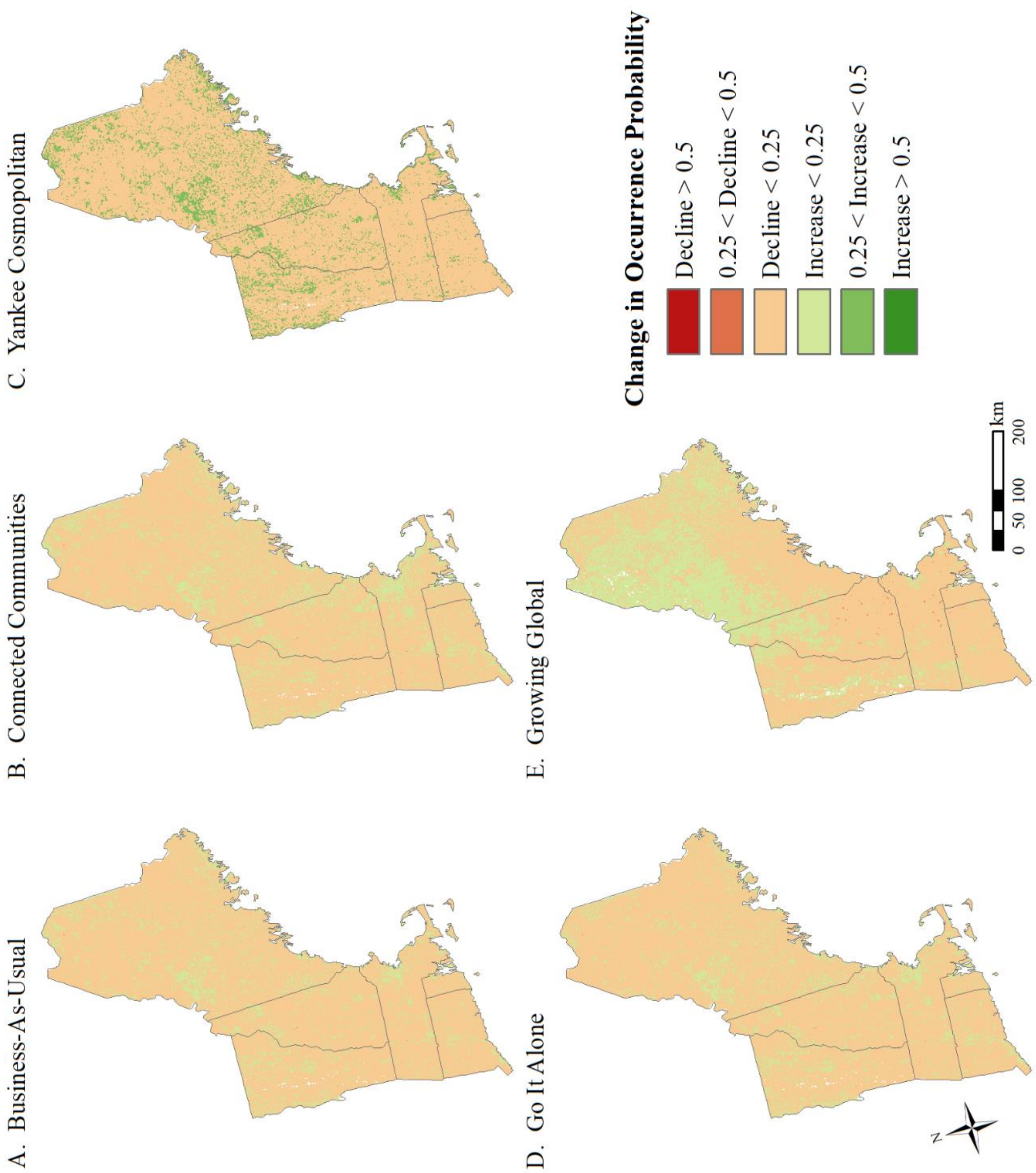
American black bear



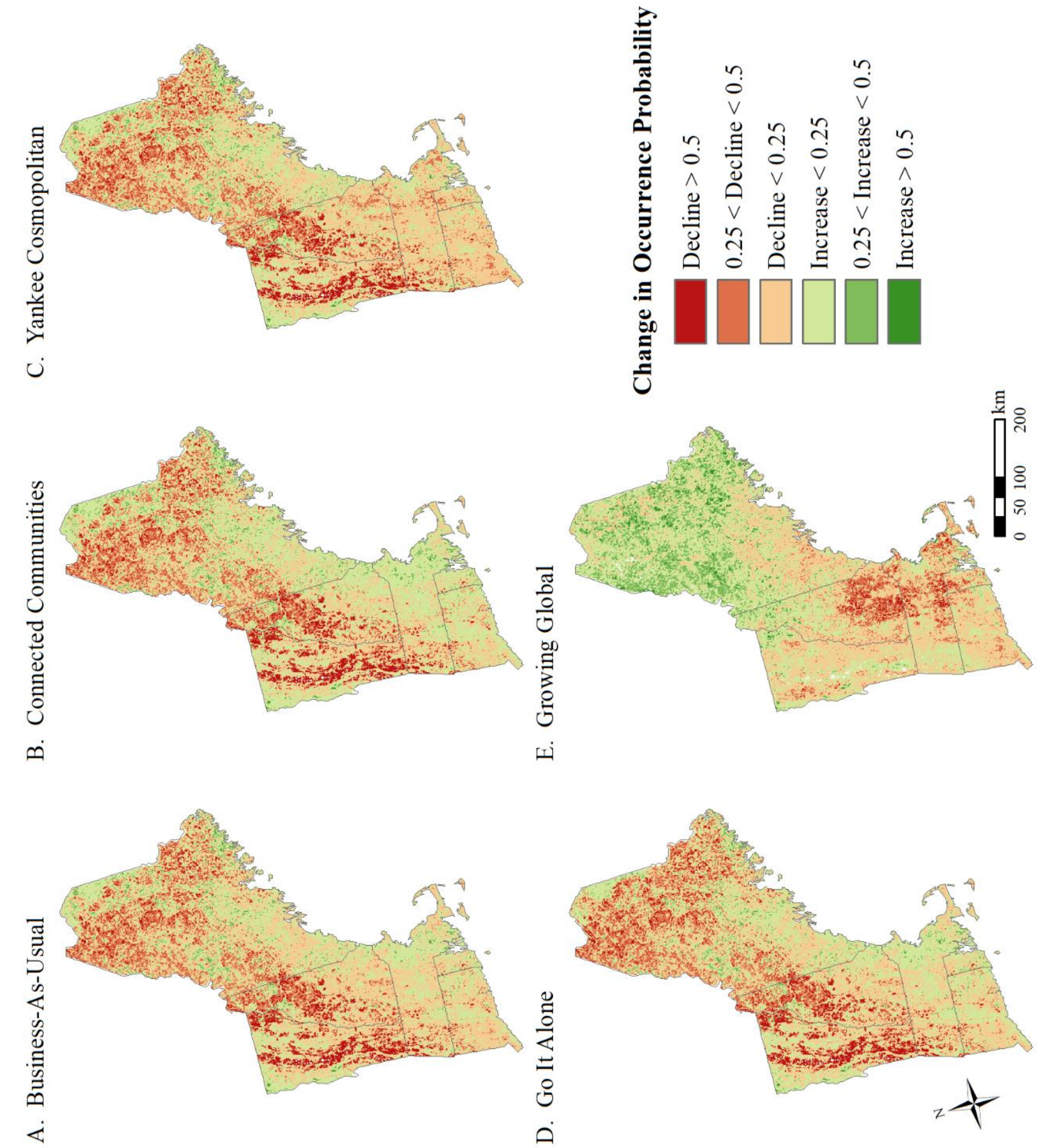
Bobcat


A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200 km
N

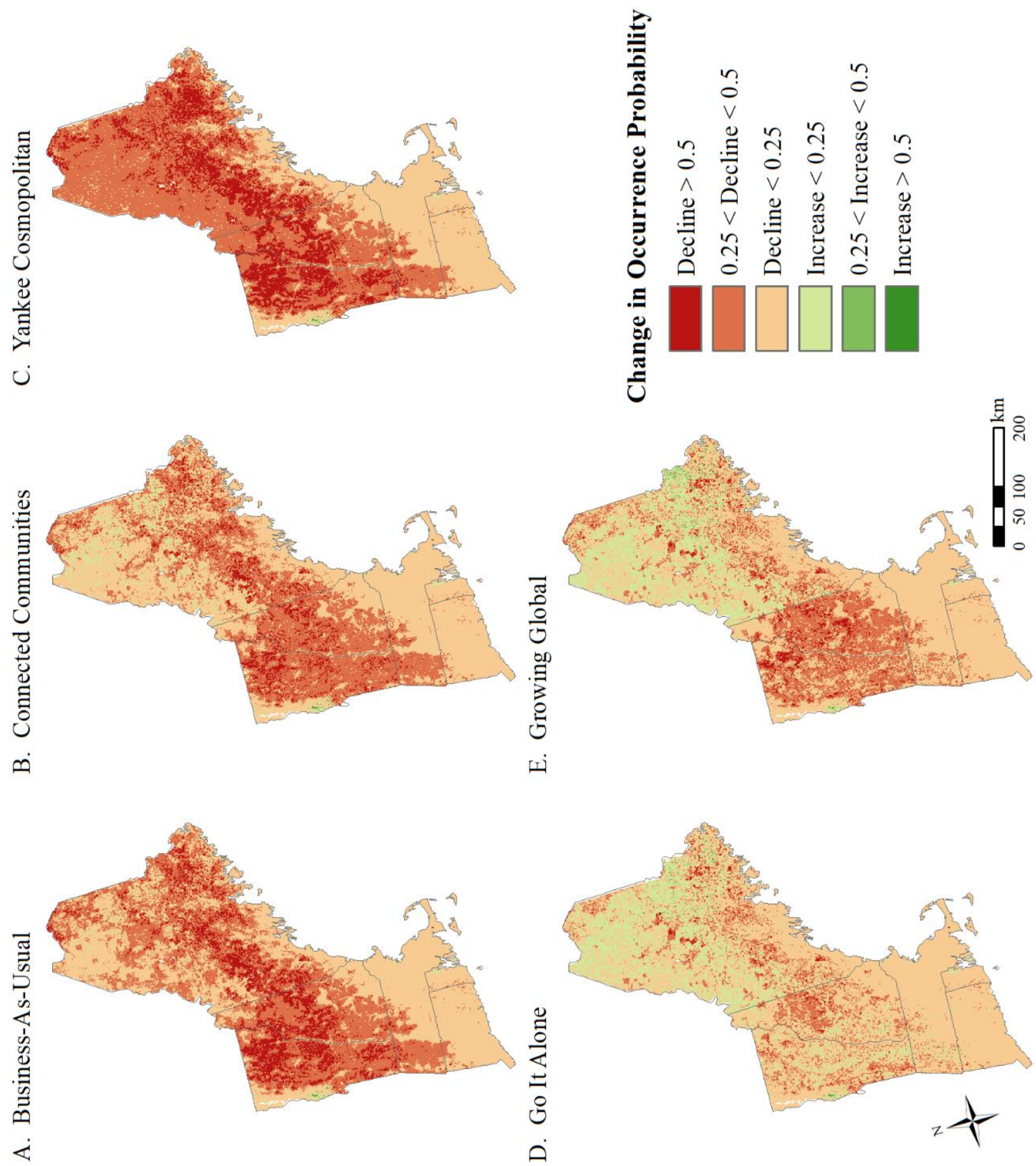
Coyote


A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200
km
N

Gray fox

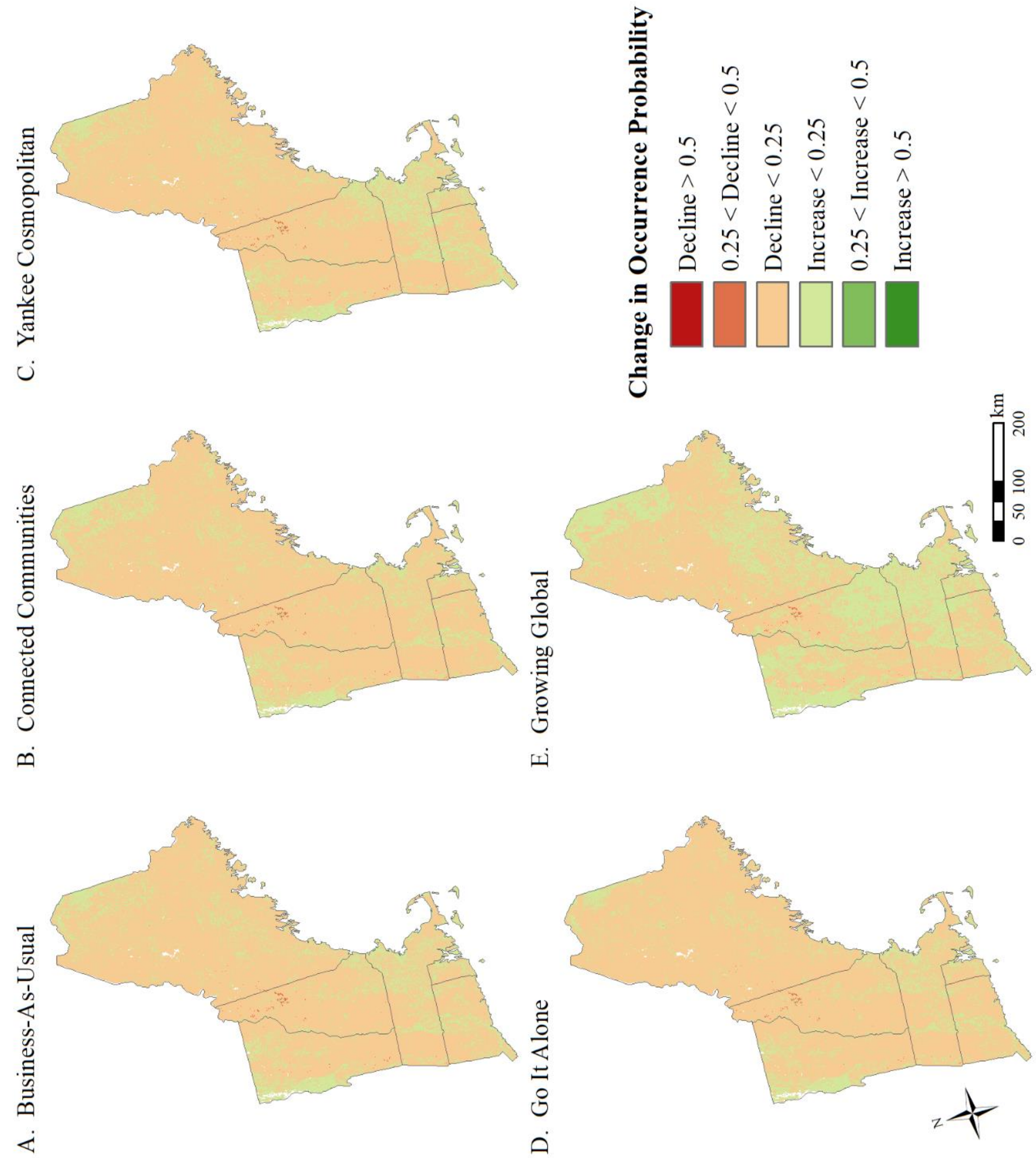

A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200
km
N

Moose



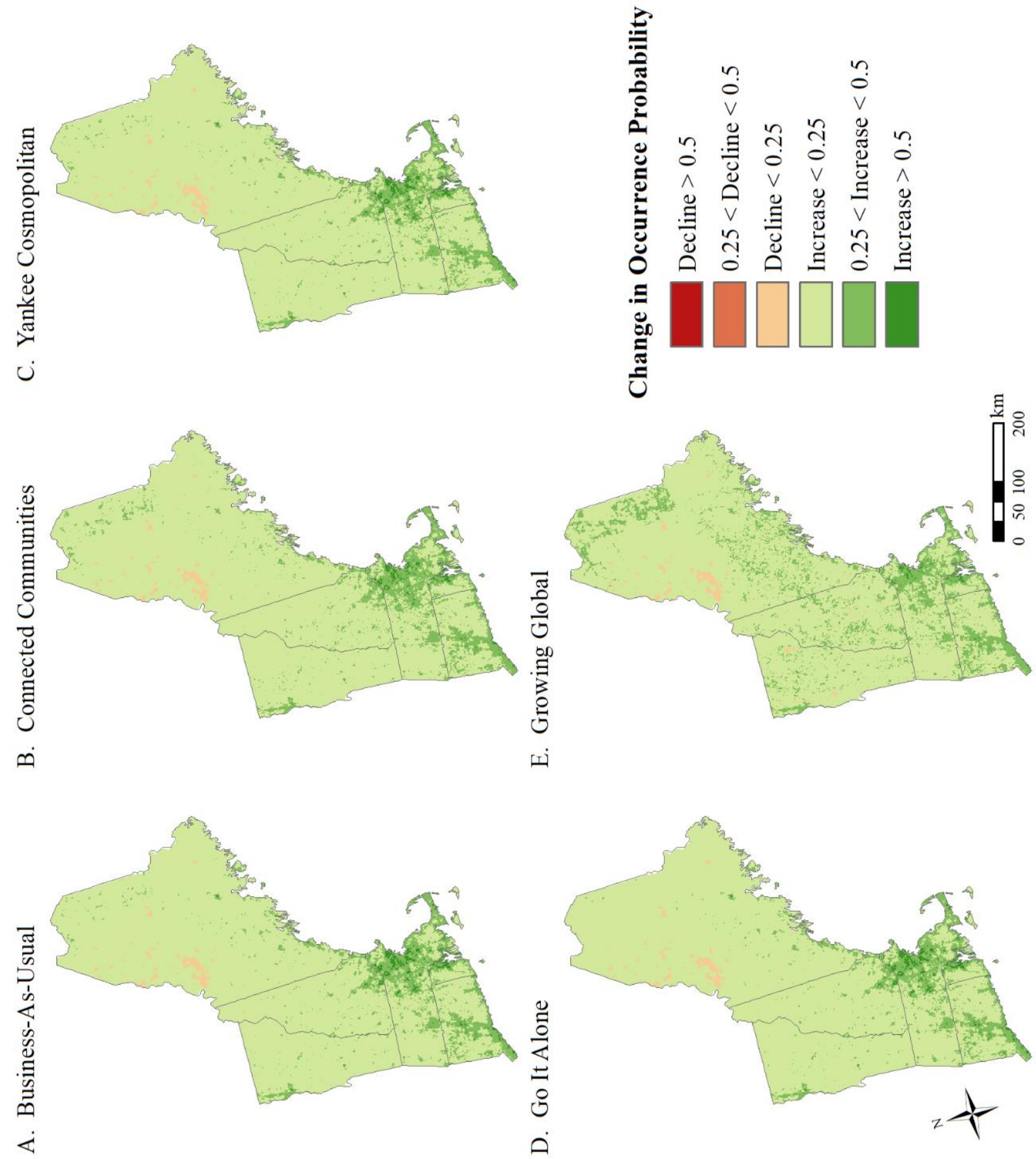
A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200 km
N

Raccoon

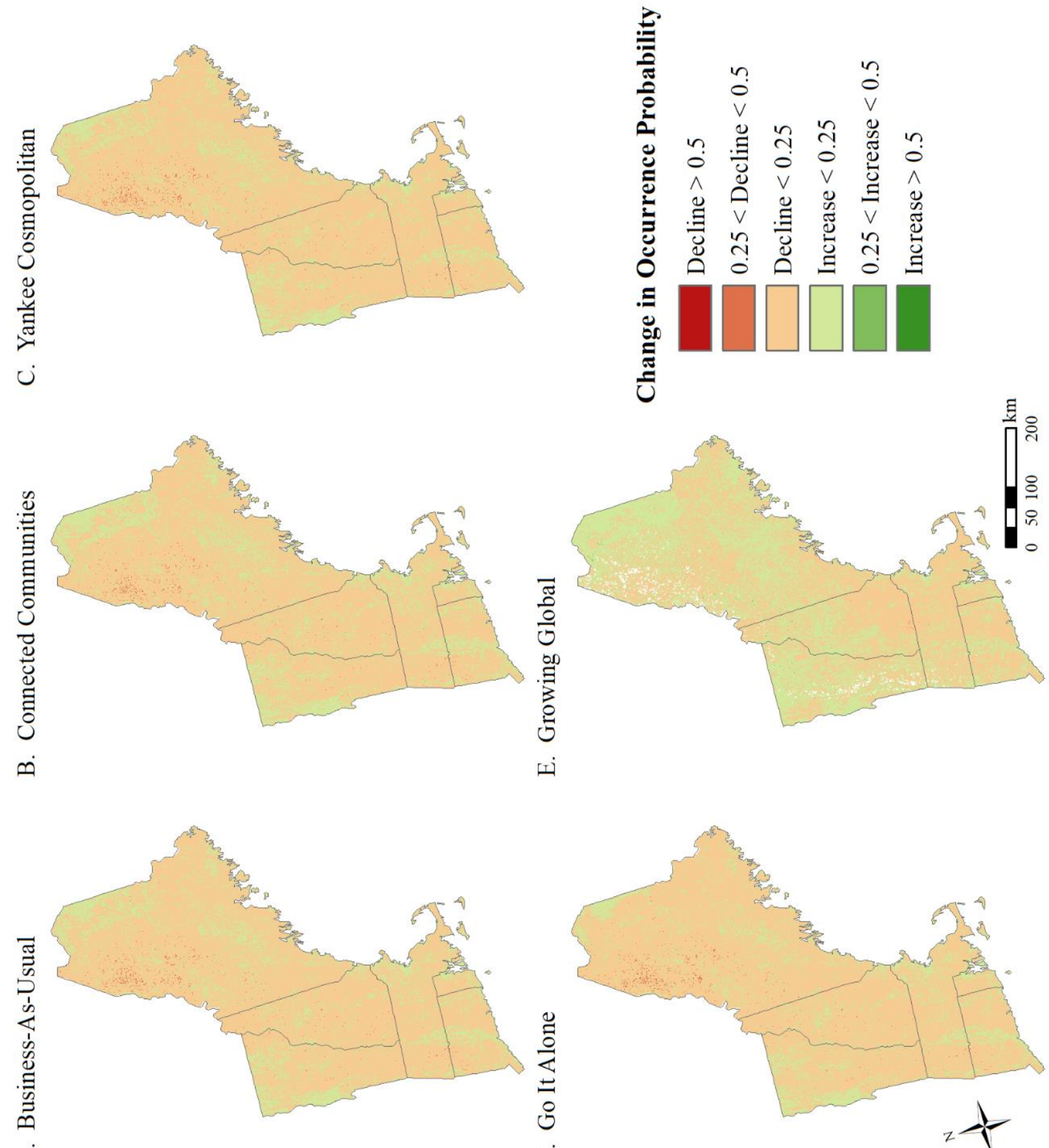


A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200 km
N

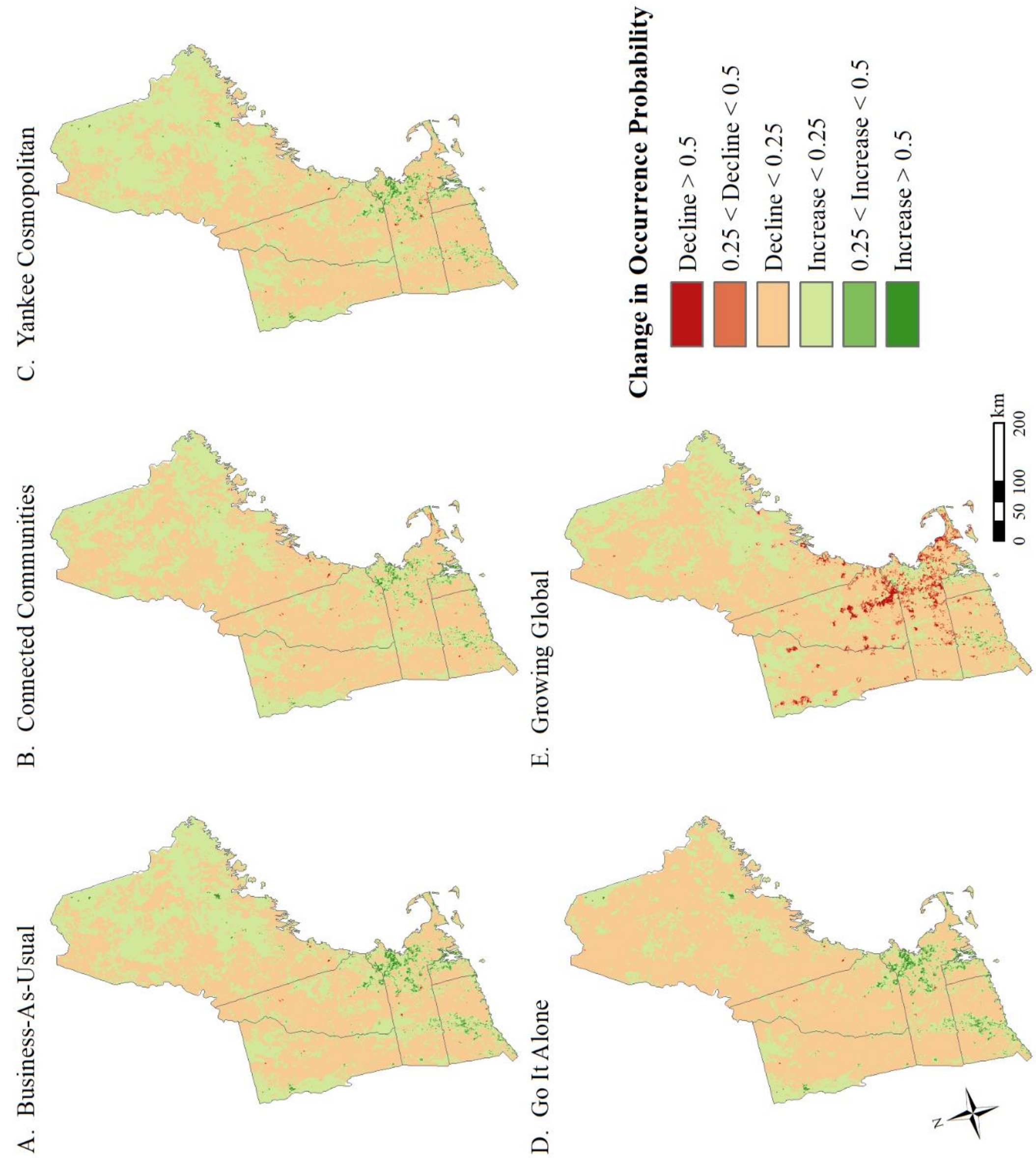
Red fox


A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200
km
N

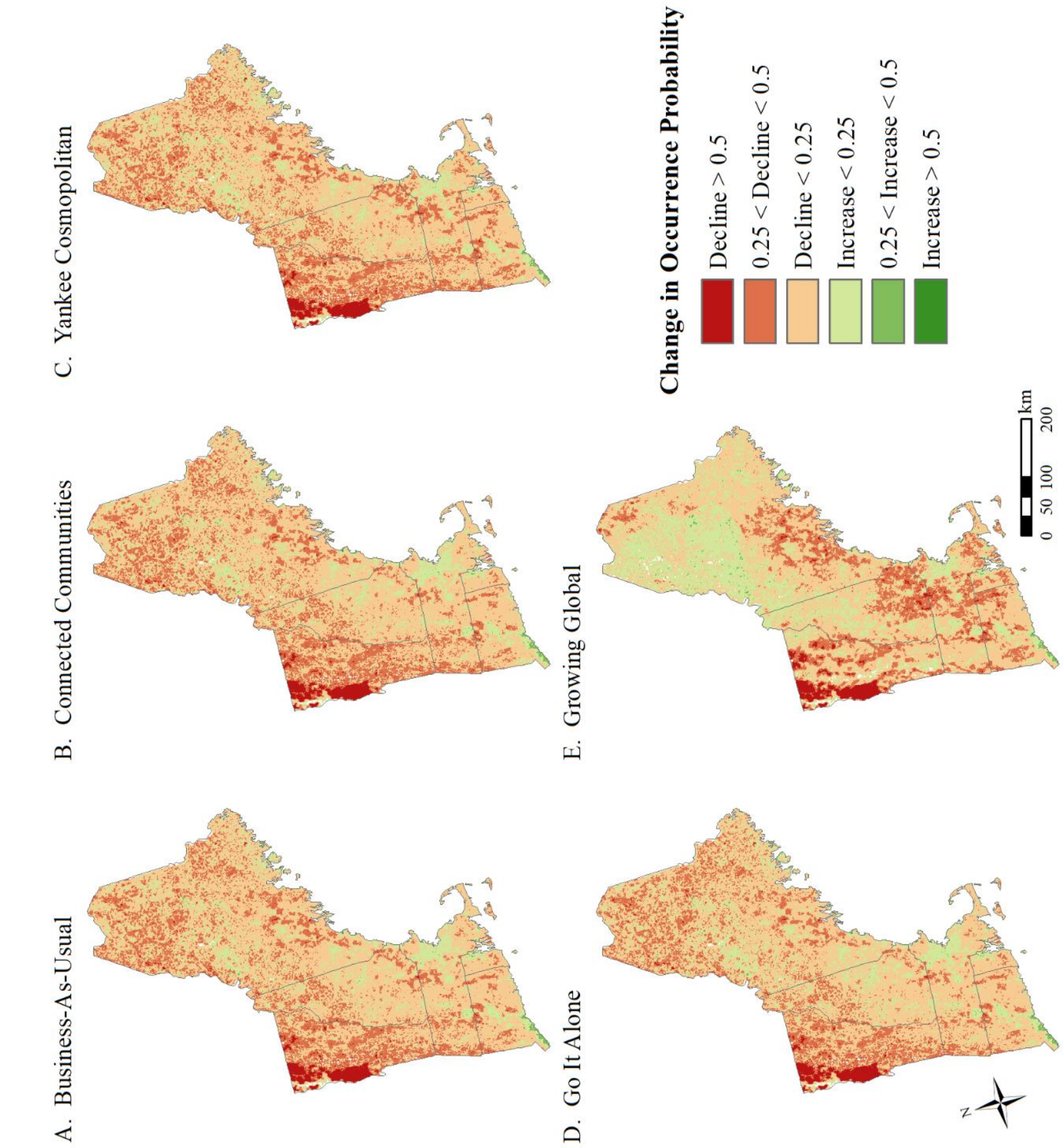
Striped skunk



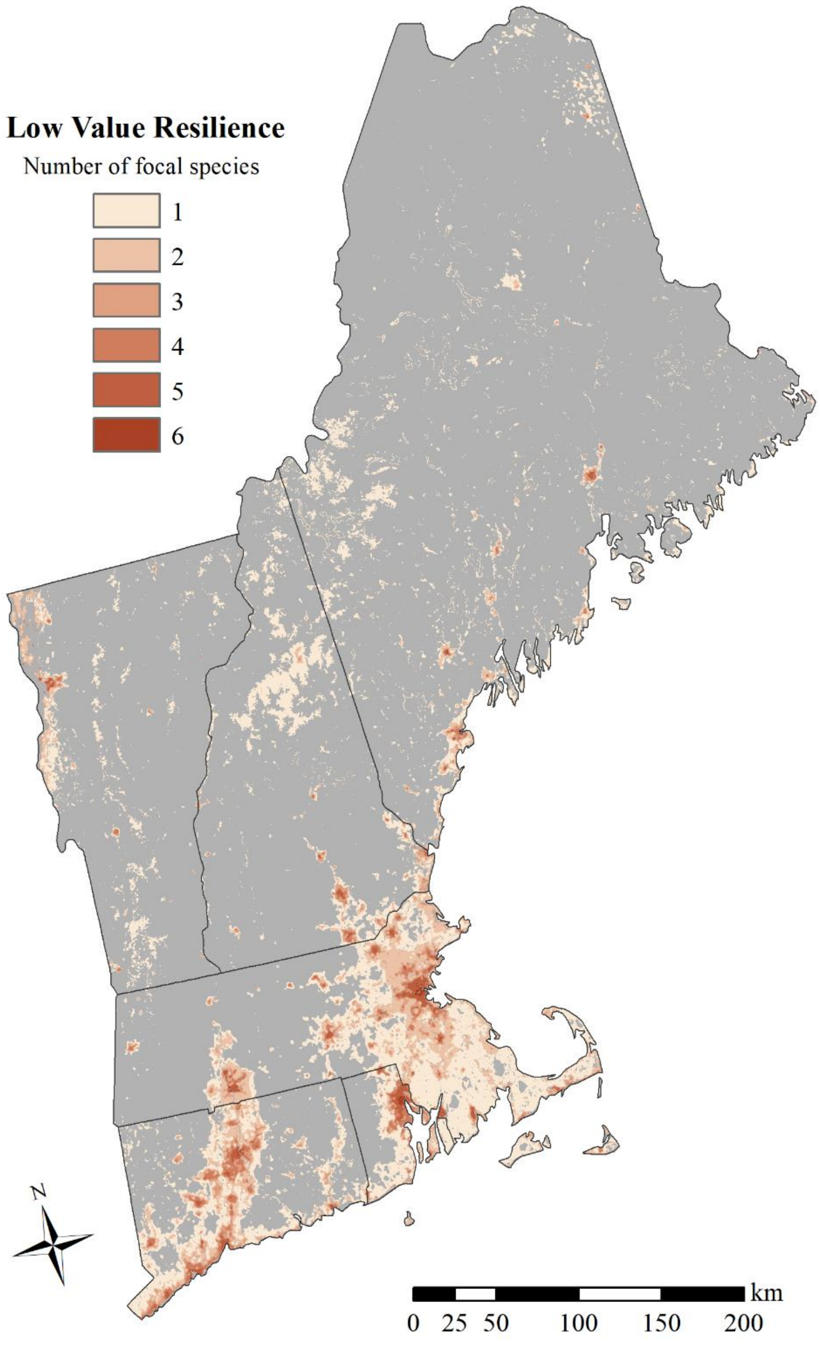
White-tailed deer



Wild turkey


A. Business-As-Usual
B. Connected Communities
C. Yankee Cosmopolitan
D. Go It Alone
E. Growing Global
Change in Occurrence Probability
Decline > 0.5
0.25 < Decline < 0.5
Decline < 0.25
Increase < 0.25
0.25 < Increase < 0.5
Increase > 0.5
0 50 100 200
km
N

D.2. Low-value areas for 10 wildlife species in the New England region of the northeastern United States. Map values indicate the number of focal species that simulated consistently low occurrence (for that map cell) under recent conditions and all five NELFP scenarios. Observed values ranged between 0 and 6 – a value of 6 indicates that the cell was designated as "low-value resilient" for 6 of the 10 focal species.



D.3. Protected parcels ranked in terms of resilience protection for 9 wildlife species in the New England region of the northeastern United States. Protected parcels were ranked by a resilience index, derived from species mean resilience within a given parcel and the number of resilient cells within the parcel. More than 57,000 protected parcels were assessed throughout New England; only the ten most resilient parcels were displayed for each species.

American black bear

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	White Mountain National Forest	Federal	Fee	NH	2.12E+09	0.70
2	Moosehead Region Conservation Easement	Joint	Easement	ME	1.45E+09	0.80
3	Upper St John River Watershed	NGO	Fee	ME	6.44E+08	0.97
4	Baxter State Park	State	Fee	ME	4.99E+08	0.99
5	Pingree Working Forest	Joint	Easement	ME	4.00E+08	1.00
6	Katahdin Woods And Waters National Monument	Federal	Fee	ME	3.62E+08	0.84
7	Katahdin Forest	Private	Easement	ME	7.66E+08	0.56
8	Pingree Working Forest	Joint	Easement	ME	2.21E+08	1.00
9	White Mountain National Forest	Federal	Fee	ME	2.18E+08	0.93
10	State Of New Hampshire	Federal	Easement	NH	1.59E+08	0.98

Bobcat

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	White Mountain National Forest	Federal	Fee	NH	2.12E+09	0.09
2	Mount Chocorua Scenic Area	Designation	Designation	NH	2.49E+07	0.66
3	Dead Creek Wildlife Management Area	State	Fee	VT	1.13E+07	0.83
4	Pemigewasset Wilderness	Designation	Designation	NH	1.21E+08	0.25
5	Pingree Working Forest	Joint	Easement	ME	3.28E+08	0.11
6	Ossipee Mountain Tract	-	Easement	NH	2.16E+07	0.34
7	Dundee Forest	NGO	Fee	NH	2.10E+06	0.94
8	Trout Pond	-	Easement	NH	1.05E+07	0.42
9	Vermont Land Trust Easement	Private	Easement	VT	2.28E+06	0.89
10	White Mountain National Forest	Federal	Fee	ME	2.18E+08	0.09

Coyote

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Moosehead Region Conservation Easement	Joint	Easement	ME	1.44E+09	0.67
2	White Mountain National Forest	Federal	Fee	NH	2.12E+09	0.51
3	West Branch	Private	Easement	ME	1.13E+09	0.54
4	Katahdin Forest	Private	Easement	ME	7.66E+08	0.60
5	Connecticut Lakes Headwaters	-	Easement	NH	6.70E+08	0.57
6	Pingree Working Forest	Joint	Easement	ME	3.28E+08	0.69
7	Upper St John River Watershed	NGO	Fee	ME	6.22E+08	0.48
8	Katahdin Woods And Waters National Monument	Federal	Fee	ME	3.62E+08	0.55
9	Green Mountain and Finger Lakes National Forests	Federal	Fee	VT	1.02E+09	0.30
10	White Mountain National Forest	Federal	Fee	ME	2.18E+08	0.59

Gray fox

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Military Training Area Camp Edwards	Designation	Proclamation	MA	8.00E+07	0.48
2	Myles Standish State Forest	State	Fee	MA	1.80E+07	0.97
3	Myles Standish State Forest	State	Fee	MA	7.57E+06	0.88
4	Quabbin Reservoir	State	Fee	MA	2.02E+08	0.17
5	Wompatuck State Park	State	Fee	MA	8.90E+06	0.79
6	Myles Standish State Forest	State	Fee	MA	4.20E+06	0.94
7	Montague Plains Wildlife Management Area	State	Fee	MA	6.13E+06	0.75
8	Quabbin Reservoir	State	Fee	MA	1.88E+07	0.42
9	Cape Cod National Seashore	Federal	Fee	MA	9.17E+07	0.17
10	Blue Hills Reservation	State	Fee	MA	7.10E+06	0.59

Raccoon

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Katahdin Forest	Private	Easement	ME	7.66E+08	0.28
2	Acadia National Park	Designation	Fee	ME	1.22E+08	0.64
3	Katahdin Woods And Waters National Monument	Federal	Fee	ME	3.62E+08	0.36
4	Military Training Area Camp Edwards	Designation	Proclamation	MA	8.00E+07	0.61
5	Debsconeags Matrix	NGO	Fee	ME	1.63E+08	0.40
6	Miscellaneous Municipal Lands	Local Government	Fee	ME	8.01E+07	0.56
7	Missisquoi National Wildlife Refuge	Federal	Fee	VT	2.84E+07	0.88
8	Cape Cod National Seashore	Federal	Fee	MA	9.17E+07	0.46
9	Allagash Wilderness Waterway State Park	State	Fee	ME	8.36E+07	0.47
10	Pingree	Private	Easement	ME	1.02E+08	0.40

Red fox

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Katahdin Woods And Waters National Monument	Federal	Fee	ME	3.62E+08	0.20
2	Dead Creek Wildlife Management Area	State	Fee	VT	1.13E+07	0.71
3	Milestone Cranberry Bog	NGO	Fee	MA	3.10E+06	0.97
4	Vermont Land Trust Easement	Private	Easement	VT	1.81E+06	1.00
5	Farm and Ranch Lands Protection Program	Private	Easement	VT	1.79E+06	1.00
6	Vermont Land Trust Easement	Private	Easement	VT	1.72E+06	1.00
7	Vermont Land Trust Easement	Private	Easement	VT	1.70E+06	1.00
8	Vermont Land Trust Easement	Private	Easement	VT	1.67E+06	1.00
9	Vermont Land Trust Easement	Private	Easement	VT	1.65E+06	1.00
10	Vermont Land Trust Easement	Private	Easement	VT	1.65E+06	1.00

Striped skunk

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Acadia National Park	Designation	Fee	ME	1.22E+08	0.69
2	Cape Cod National Seashore	Federal	Fee	MA	9.17E+07	0.77
3	Moosehorn National Wildlife Refuge	Federal	Fee	ME	1.18E+08	0.63
4	Miscellaneous Municipal Lands	Local Government	Fee	ME	8.01E+07	0.74
5	Military Training Area Camp Edwards	Designation	Proclamation	MA	8.00E+07	0.58
6	Spring River Matrix	NGO	Fee	ME	3.93E+07	0.72
7	Typhoon & Downeast Lakes Public Access Easement	Private	Easement	ME	7.35E+07	0.53
8	Sunkhaze Meadows National Wildlife Refuge	Federal	Fee	ME	4.65E+07	0.65
9	Typhoon & Downeast Lakes Public Access Easement	Private	Easement	ME	6.84E+07	0.54
10	Typhoon & Downeast Lakes Public Access Easement	Private	Easement	ME	7.50E+07	0.51

White-tailed deer

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Upper St John River Watershed	NGO	Fee	ME	6.44E+08	0.68
2	Moosehead Region Conservation Easement	Joint	Easement	ME	1.45E+09	0.45
3	Baxter State Park	State	Fee	ME	4.99E+08	0.66
4	White Mountain National Forest	Federal	Fee	NH	2.12E+09	0.32
5	Katahdin Forest	Private	Easement	ME	7.66E+08	0.51
6	Debsconeags Matrix	NGO	Fee	ME	1.63E+08	0.85
7	Moosehorn National Wildlife Refuge	Federal	Fee	ME	1.18E+08	0.96
8	Katahdin Woods And Waters National Monument	Federal	Fee	ME	3.62E+08	0.51
9	Baxter State Park Scientific Management Area	State	Fee	ME	1.17E+08	0.90
10	Typhoon & Downeast Lakes Public Access Easement	Private	Easement	ME	7.35E+07	0.97

Wild turkey

Rank	Unit name	Ownership	Category	State	Area (m^2)	Mean resilience
1	Kennebunk Plains	State	Fee	ME	4.11E+06	0.93
2	Burlingame	State	Fee	RI	8.99E+06	0.52
3	Wompatuck State Park	State	Fee	MA	8.90E+06	0.49
4	Parker River National Wildlife Refuge	Federal	Fee	MA	1.34E+07	0.38
5	Hammonasset River - Hfa	Private	Easement	CT	8.24E+06	0.46
6	Massabesic Experimental Forest	Designation	Designation	ME	3.26E+07	0.23
7	Machias River	Private	Easement	ME	3.62E+06	0.68
8	Rocky Gutter Wildlife Management Area	State	Fee	MA	7.24E+06	0.48
9	Blue Hills Reservation	State	Fee	MA	7.10E+06	0.46
10	Moose Mountains Reservation	NGO	Fee	NH	8.85E+06	0.39